Framework Development and Validation of Logistics Perfect Order Fulfillment in the Retail Industry

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ABSTRACT

The retail supply chains is becoming customer-centric which requires a robust Logistics Perfect Order (LPO) instrument to evaluate logistics last-mile delivery performance in the context of retail. The absence of a psychometrically validated measurement model creates a constraint in both the academe and industry. This study aimed to develop and validate a multidimensional measurement model of LPO. Using a quantitative cross-sectional design, data was gathered through simple random sampling among retail and logistics supervisors, managers, and business owners. Gathered from 461 respondents in the Exploratory Factor Analysis and 423 in the Confirmatory Factor Analysis, it was analyzed using PLS-SEM. Results showed a refined and empirically supported four-domain LPO capability architecture, consisting of Product Quality Assurance and Service Recovery (PQASR), Delivery Flexibility, Communication, and Customer Coordination (DFCCC), Customer Relationship Management and Packaging/Handling Controls (CRMPH), and Route Planning, Forecasting, and Operational Reliability (RPFor). The results indicated that delivery quality and recovery mechanisms comprise the most influential LPO dimension, while technology serves as an enabler integrated among various dimensions rather than act independently. The final framework provides a valid and reliable model to assess the performance of the retail last-mile delivery and is recommended for application and more validations across diverse retail logistics settings.

Keywords: business administration, EFA-CFA, last-mile logistics, retail industry, Logistics Perfect Order, measurement model

. Introduction

The Logistics Perfect Order (LPO) construct was introduced by various authors as an all-encompassing performance measurement in retail logistics to capture metrics such as timeliness of delivery, completeness of orders, product quality, and accuracy of documentation (Bowersox et al., 2016; Chopra & Meindl, 2018). However, the dimensions are not uniformly measured in actual practice in different industries, resulting in disjointed logistics effectiveness meanings. The literatures highlight planning, forecasting, and scheduling as the core business drivers of logistics excellence (Mentzer et al., 2001; Bowersox et al., 2016; Christopher, 2016; Chopra & Meindl, 2018).

The said studies likewise demonstrate that the quality of execution, service recovery, and real-time coordination have greater and more direct impact on perfect order results compared to pre-delivery planning only.

Thus, there is a need to develop a LPO model with the rapid expansion of retail and heightened customer expectations. Its strategic importance had been emphasized by scholars the creation of an effective measurement model to identify critical operational capabilities, support continuous improvement, and enhance competitiveness (Kaplan & Norton, 1996; Gunasekaran et al., 2004; Neely et al., 2005). It was also highlighted by Christopher (2016) pointing out that customer value in supply chains increasingly require consistent good delivery performance more than cost efficiency alone. In similar token, Mentzer et al. (2001) highlighted the need to develop integrated logistics capabilities. As retail continues to evolve including the development of digitalization and predictive analytics to ensure customer-centric service strategies, there is an urgent need to develop a Logistics Perfect Order (LPO) measurement model.

At the onset, contemporary last-mile delivery logistics environments are becoming complicated in terms of the accelerating digital transformation, the rise of the omnichannel retailing, and the heightened demands of consumers in terms of speed and visibility (Liu et al., 2021). Other reviewed literatures also suggested that a more holistic and capability-grounded performance models should be proposed instead of the fixed key performance indicators, dynamic, and multidimensional models with the inclusion of execution, adaptability, and the transparency of information (Cusihuaman-Torres et al., 2023). This study provides answers and empirical proof that LPO fulfillment is not a one-dimensional measure but rather a system of interdependent operational competencies.

The LPO as an academic topic among colleges and universities remains underrepresented in the courses logistics, supply-chain and operations-management courses even though it is widely used in the industry (Magnaye & Varma, 2020). The lack of connection can be referred to more theoretical, methodological and contextual anomalies. In academic research, a many studies treat LPO as an aggregate measure in contrast to being a multidimensional construct that has more explanatory power and cross-context comparability (Christopher, 2016; Pagell & Wu, 2020). Furthermore, many academic studies were conducted among first world economies. LPO studies involving psychometric validation among developing and emerging economies where there are more challenges in the infrastructure variability, market fragmentation, and policy issues that affects logistics performance (Lim et al., 2018; Nguyen et al., 2021). The proposed research bridges the gap between the theory and practice by empirically supporting a four-dimensional LPO framework under the Philippine retail setting. Findings of this research demonstrated a capability approach to research that would align research with the reality of the last-mile logistics system and retail logistics system.

Gaps in Literature. The LPO has been referred to numerous times in the lieratures but in most cases it has been referred to in a hypothetical manner without much empirical validation. Various researches perceive LPO as one aggregated measure and fail to think of it as a multidimensional measure that entails timeliness, completeness, accuracy, and product condition as its measurable elements (Christopher, 2016; Hosseini et al., 2019). This brings to focus the need to have a research that would prove LPO to be a latent measure by use of sound techniques like EFA and CFA. In many research articles, the outcome variables which is LPO is defined without the development of scales or construct validation models (Pagell & Wu, 2020; Hosseini et al., 2019).

Another gap is the situational gap. The LPO research concentrates on the developed markets where infrastructures, regulations and customer expectation differ greatly versus emerging markets. The studies by Lim et al. (2018) and Nguyen et al. (2021) suggest that infrastructure variability, market fragmentation, and the inability to enforce the policy are some of the factors that affect the performance of logistics in emerging economies such as Southeast Asia. Thus, there is insufficient studies regarding the operation of LPO in countries like the Philippines in the retail logistics sector.

UN SDG. The study is anchored on some United Nations Sustainable Development Goals (SDG/s) notably SDG 9 on industry, innovation, and infrastructure and SDG 12 on responsible consumption and production. The validation of LPO had technology-enabled logistics, digital transformation and operational excellence. The last-mile delivery environment promotes the innovation of logistics measurement through the combination of real-time monitoring and customer-oriented measurements in the study. It also seals any loopholes within the logistics infrastructure and measurement systems in developing countries, aids in the development of resilient infrastructure and encourages sustainable inclusive industrialization.

Theoretical Underpinnings. The study is anchored upon the Logistics Service Quality (LSQ) Framework by Mentzer et al. (1999). The LSQ fits traditional service quality models such as SERVQUAL to business logistics by emphasizing on service implementation in business logistics. Mentzer et al. described the quality of logistics services as the overall rating of a customer on the effectiveness of a provider to satisfy or surpass expectations in the touchpoints of delivering services. The model LSQ incorporates the nine dimensions that comprise the quality of information, timeliness, order condition, order accuracy, order discrepancy handling, personnel contact quality, order quality, convenience, and customer complaint handling. These are the fundamental areas which influence customer satisfaction directly. Numerous of such dimensions, such as timeliness, accuracy, ordinal condition, and completeness, correlate well with the elements of Logistics Perfect Order (LPO), which is why LSQ is a very relevant framework when analyzing last-mile delivery.

The LSQ has been tested in other situations. It has been used by Thai (2013) on maritime logistics, Liu et al. (2021) on Chinese e-commerce, Shang and Lu (2012) on last-mile urban delivery, and Rahman et al. (2021) on third-party logistics. These analyses employed EFA and CFA to verify that LSQ has a dimensional structure, which is sound and flexible. LSQ is suitable in the retail field as it is based on operational logistics implementation, which is the basis of LPO measures. Because flawless accomplishment of orders involves correct product, in correct condition, at correct moment, and in correct amount then LSQ dimensions serve as motivators towards accomplishment of LPO.

The theory presumes that the quality of logistics services is multi-dimensional. It assumes the dimensions of timeliness, accuracy, condition, the quality of communication and the quality of customer service, which will all play a unique role in the perceptions of customers. It also associates service performance with customer satisfaction and loyalty. The quality of logistic services increases the level of satisfaction, and as a result, the level of loyalty and repeat purchase. Reliability and consistency orders are delivered right, on time and in good condition are indicators of LSQ. Small failures in these respects may cause a loss of confidence. Last but not the least, LSQ may be measured by a system of customer feedbacks and performance indicators, which allows the organizations to focus on a particular aspect (communicateon, responsiveness, handling) and gain even greater satisfaction.

Objectives of the Study. The objectives of the study are threefold which includes to discover the latent dimensions of the Logistics Perfect Order (LPO) in the sphere of retailing; to measure and test a measurement scale with reference to the dimensions; and to evaluate the construct and reliability validity of the LPO model in relation to the last-mile delivery in retailing.

Significance of the Study. The results were expected to create an impact on the academe, retail sector practitioners, and the researchers. First, it can be used by the academe to improve the insights into the logistics and quality of services by developing context-specific LPO measurement model. Although the literature in this area typically focuses on the measurement of supply-chain in general or theoretical concepts, the present study offers empirical data of the specific dimensions of LPO as they manifest themselves in last-mile delivery processes. It provides a strong scholarly basis of logistics performance measurement and provides a sophisticated conceptualization that can be applied by educators and students of business, supply chain and operations management in the context of learning how delivery excellence is attained and measured in the retail industry.

This study also provides a useful resource to evaluate and optimize LPO. This is specifically to practitioners in the retail industry, including logistics managers, delivery managers, owners of brick-and-mortar stores, and participants in last-mile logistics. The detection and confirmation of certain dimensions including timeliness, accuracy, condition, completeness, and information quality will help retailers to improve their delivery processes, customer satisfaction, and service failures reduction. The performance-management systems also take cognizance by the findings of this study that will assist in optimizing the logistics strategies and aid in decision making pertaining to outsourcing, technology adoption and process improvement in delivery operations.

METHOD

Research Respondents. In the qualitative section, the participants of the study consisted of the retail store owners, logistics managers, and logistics professionals, all of whom were directly involved in the logistics and delivery operations in the retail industry. The respondents were all working in Davao City. They were employed due to their operations and managerial functions expertise, which gave a thorough insight into LPO, including delivery promptness, order accuracy, completeness, and product condition. The study by Kilibarda et al. (2020) noted that logistics professionals and managers are in the best position to measure logistics performance indicators since it is in their main areas of work to create, run, and evaluate logistics plans.

In the quantitative section, there is the involvement of retail-level participants including supervisors and store owners provides valuable information in how the performance of logistics impacts the end-customer satisfaction and continuity of day-to-day business (Asamoah et al., 2021). On the same note, using multi-level retail stakeholder data is important in estimating service performance since store-level staff members have the contextual understanding of customer-facing logistics performance (Jaiswal & Singh, 2020). The presence of this heterogeneous population of respondents guaranteed the gathering of precise sensitive data which is correctly based on experience and fostered more reliable and valid evaluation of LPO within the retail context.

The research participants are from Davao City. The city was chosen as it is the largest and most economically important city in the region and in the southern part of the Philippines. It is referred to as the business and trading capital of Mindanao and it has a fast-growing retail industry, which is constituted by various local businesses, national chains, and multinational retail companies. In addition, the Philippine Statistics Authority (2025) highlighted that the city has been recording a steady retail growth throughout the past 10 years, with the emergence of shopping centers, convenience stores, and online stores contributing to the growth of logistics processes. It is these reasons that enable Davao to serve as a great location to assess the potential of LPO since the logistics and delivery systems of the city play a significant role in supporting the ever-increasing needs of both retailers and consumers.

Furthermore, the geographic position of Davao and its strategic significance as a power junction point of both inland and maritime trade routes is a complex logistics problem, which makes the city the right place to research the issue of last-mile delivery and its performance indicators. Having a vivid retail orientation and building infrastructural development that has been in progression, such as road widening and new constructions, the study was able to get the information that encompasses a wide range of retail logistics stakeholders. All these make Davao pertinent besides being in a strategic position to measure and validate LPO in the Philippine retail environment.

The inclusion criteria included participants must be in the retail industry who were engaged in logistics business. They may be owners of retail stores, logistics executives, logistics experts, and store managers as they have the first appropriate experience in the last-mile delivery processes, fulfillment of orders, and the performance of logistics. The very idea behind inclusion is that of the expert judgment is relevant to the study and richness of experience of the respondents are taken into account as the factors of higher importance (Etikan et al., 2016). The retail operations will have to be where the manager or owner works which is in Davao City. The study, however, excluded those individuals who did not supply informed information and who were not directly linked to the retail logistics. It is critical to the measurement development in logistics that respodents have experiences in decision making/execution is relevant or customers, or employees (Taherdoost, 2016). Moreover, the participants with less than six months experience in their current job of logistics were excluded since they may not be well informed to provide the required answers aligned with the recommendation of Daniel (2019).

The results of the study showed a demographic population of 461 people in the EFA section. The gender distribution is nearly balanced, with 48.4 and 51.6 percent of male and female participants, which is almost similar to the gender distribution of the total population of Davao City. This indicates that it does not have gender bias. The sample size distribution is skewed towards the 35-54 years old (70.7%), implying that the majority of the participants are within the economically productive and decision-making years of the professional experience and have a significant volume of experience training regarding the reliability of delivery, accuracy of the orders and service recovery practices.

The demographic profile likewise indicates that the functions are primarily managerial and supervisionary with the respondents having positions like head of operations, sales supervisors and the logistics or supply chain managers on the frontline, among more than 10 other position titles. The positions are important in getting perceptions inspired by those who have direct responsibility towards results in delivery, inventory management and customer service. The competence of respondents is also grounded on the organizational tenure where over 70 percent of the respondents have 4-9 years of organizational experience. It is a balance between the new workers and long-term practitioners, respectively, which captures the need for knowledge in operations and strategic organizational strategy. The organizational environments are also heterogeneous where most of the respondents are representatives of small-and-medium-sized businesses, however, there are also medium-sized organizations that augment the external validity of various degrees of formalization of processes and resource base.

Organization-wise, although a limited number of companies have logistics or supply chain departments, the majority of the companies distribute the functions within the existing managerial duties and cross-functional alignments which are not logistics department. Operational activities also indicate a high logistical maturity, where majority of the firms outsource their last-mile delivery services to a third party, and also undertake monthly or quarterly performance appraisals. Taken as a whole, these attributes signal a heterogeneous but highly relevant respondent base whose demographic, organizational and operational heterogeneity augments construct stability, content validity, and generalizability of the suggested LPO measurement model in the context of the actual retail and logistics setting of Davao City.

The CFA phase using simple random sampling approach made sure the responses are received by individuals who possess expert level of knowledge in terms of retail logistics. The CFA level had 423 respondents. The researcher target measurement validation and model testing, thus, the suitability of respondents were given more importance than their suitability to represent the entire population (DeVellis, 2017; Etikan et al., 2016). The method is also appropriate because the CFA aims at establishing the composition and associations between latent variables on the basis of the information presented by qualified practitioners. Retail store owners, logistics professionals, logistics managers, and supervisors engaged in the operations of the last-mile delivery of goods in Davao City were the target respondents, as is the case with the EFA phase.

Instrument/Material. The qualitative section used a semi-structured interview guide was used which helped in getting in-depth information on the key informants who participated in logistics and delivery operations. The tool is an open-ended questions structured based on the literature covering timeliness, order completeness, responsiveness, and technological integration.

The guide is flexible in that the researcher had dug deeper into the emerging themes on all the critical areas concerning logistics performance. According to Creswell and Poth (2018), semi-structured interviews are suitable in the context of a qualitative research study as they are organized enough to provide a rich collection of narrative data and simultaneously free enough to leave the topic of discussion open-ended and enable participants to express their lived experience using their own language. The tool was validated by experts to provide clarity, relevance and compatibility of the research goals, which increases its content validity and usability in the thematic analysis. In the study by DeVellis (2017), the author said that such closed-ended instruments are necessary to resolve the consistency, comparability, and quantifiability of responses in a large sample.

In the quantitative section, the research tool was designed to evaluate the perceived performance of various dimensions of delivery. It is a structured survey questionnaire with 90 items evaluated using the 5-point Likert scale of Strongly Disagree to Strongly Agree. The questions in the EFA section were items from the interview of the IDI in the qualitative section as well as from the pieces of literature reviewed. The EFA items consisted of items based on the interview responses and validated by different theoretical frameworks, such as Lim et al. (2018), Hubner et al. (2016), Esper et al. (2019), and Nguyen et al. (2021). Expert validation of questionnaire also involved conducting content validation on the questionnaire to guarantee that it measures its constructs in a manner that it is appropriate and that it is valid on a large scale to be administered. The professional validation was also useful in making the survey items understandable, applicable as well as dependable especially when it comes to the measurement of latent constructs such as the Logistics Perfect Order (LPO).

The reliability testing is an important procedure in guaranteeing the quality of the research results. This process are important in quantitative research, as stressed by some authors (Creswell & Creswell, 2018; Hair et al., 2019). In addition, the authors likewise pointed out that data validation must help explain the accuracy and consistency of the collected data. Within the framework of this research on LPO in Davao City, data validation was conducted by careful data entry, cleaning, as well as, data verification in order to detect and correct any mistake or inconsistency in the data set. This is through verification of missing records/data, verification of outliers and uncongruent records.

The conduct of reliability testin was highlighted as an import part of a study especially when conducting survey-based research on structured survey tools (Creswell & Creswell, 2018; Hair et al., 2019). Thus, to determine the reliability of the research instrument, methods like the Cronbach's alpha was used to determine the internal consistency of the survey questions pertaining to variables. The scores of the internal consistency reliability test of the Logistics Perfect Order (LPO) measurement instrument showed that the overall Cronbach's alpha coefficient was 0.939 using 90 items that is very high, much more than the commonly recognized 0.70 internal consistency level in exploratory research and 0.80 internal consistency level in established scales (Tavakol et al., 2011; Hair et al., 2019). This finding indicates that the measures in the instrument are very correlated and they are always suitable to measure the constructs that are of interest in terms of performance in logistics and perfect order fulfillment.

In the scale development terms, the high alpha value is a sign of a high degree of coherence between items, which means that the respondents perceive the items in a consistent and stable way (DeVellis, 2017; DeVellis & Thorpe, 2021). The high reliability score, in terms of the current study, which took place in Davao City, suggests that the LPO items have a good understanding among the respondents regardless of their retail formats, organizational size, and position in the organization, even when the level of logistics formalization and availability of resources is different.

The methodological literature highlights that extremely high alpha greater than 0.90, needs to be considered as well in order to make sure that the items are not too full of redundancy (Tavakol & Dennick, 2011). Taking into consideration the multidimensional character of the LPO construct, which encompasses delivery timeliness, accuracy of order, completeness, condition, coordination, and service recovery, the high alpha in the present research is rather related to the comprehensive and well-integrated item pool instead of redundancy (Bowersox et al., 2016; Christopher, 2016). It goes along with the best practices in the early-scale development of the scale in which broader item coverage is suggested before the scale is purified with the help of exploratory and confirmatory factor analyses (Boateng et al., 2018; Worthington and Whittaker, 2006).

Research Design. The research design used in this study is a combination of qualitative and quantitative research to formulate and test a model of measuring Logistics Perfect Order (LPO) in the retail sector. In the Qualitative section, it was used only for thein-depth interviews (IDIs) used to collect data by interviewing logistics experts with ideas and opinions related to last-mile logistics. The Quantitative section likewise provided opportunity to measure relationships between variables systematically, and statistically analyze them, which is necessary to develop a model that reflects observable indicators (Creswell & Creswell, 2018). In this study, these indicators include timeliness, accuracy, completeness, and state of delivery. The quantitative approach also has the advantage of empirical testing the patterns and relationships of these variables.

The quantitative research employed Exploratory Factor Analysis (EFA) in order to reveal the latent aspects of LPO. The EFA is usually used to demonstrate the latent structure of a construct without the need of a developed model (Fabrigar & Wegener, 2012). It establishes patterns amongst observed variables and classify them into meaningful factors that are indicative of the main dimensions of LPO timeliness, accuracy, completeness, and the condition of the product (Worthington & Whittaker, 2006).

Then, the study also utilized Confirmatory Factor Analysis (CFA) used to test the factor structure after EFA. The CFA examined the data and determined which measures established construct validity and the robustness of the relationship between indicators and latent variables (Kline, 2016). This procedure measured the reliability, convergent validity, and discriminant validity of the model so that the model is able to reflect the Logistics Perfect Order construct of the retail setting. In addition, model indices were also reviewed. The mixed EFA-CFA model, was suggested by several authors (Hair et al., 2019) to guarantee that the resulting measurement model is empirically-based and theoretically-firm and can be regarded as a powerful instrument in assessing the performance of last-mile delivery using LPO in the retail sector.

Data Collection Procedure. The data for the qualitative section was gathered from key informants based on their deep-seated knowledge of logistics performance and delivery processes. It was gathered from managers of logistics, logistics supply chain managers, and a business owner. Such an approach is suitable in qualitative studies since it is more depth than breadth-focused and focuses on the choice of information-rich participants capable of providing detailed information on the constructs under investigation (Patton, 2015). The data saturation was used to decide the number of participants as no new themes may be produced by the further interviews (Guest et al., 2006). The study initially had 5 managers and 1 owner that has already achieved a level of saturation of themes. Nevertheless, the researcher added a participant to ensure there were no more new information gathered.

The quantitative section gathered the data to ensure that the sufficient and statistically significant number of responses was collected so that the Exploratory Factor Analysis (EFA) and the Confirmatory Factor Analysis (CFA) could be conducted. The sample size used the rule 5 to 10 respondents per item is considered to be enough in order to conduct EFA, and 200 is recommended in order to have a stable factor solution (MacCallum et al., 1999).

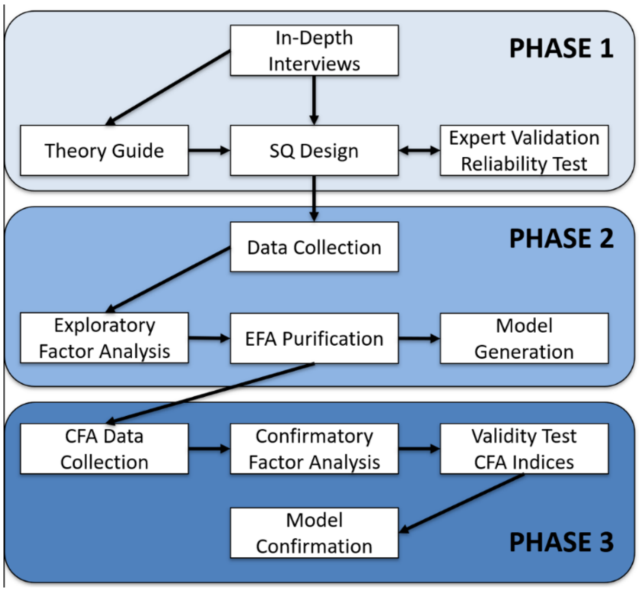
In the EFA-CFA section, the sample size ratio that was used by the researcher in this study was 5 respondents to every item with 90 items. There were 461 respondents in the EFA and 423 respondents in the CFA. According to Hair et. al, 2019, the authors observed that when n is more than 300, especially when there are few communalities or factors, more improved and consistent solutions can be drawn. The Confirmatory Factor Analysis (CFA) works better with larger samples (300 or above) to enhance the model fit indices (Kline, 2016). The respondents were introduced to the survey in a structured survey instrument in Likert scale format and the results were then subjected to the validity and reliability testing after which they were included in the structural equation model.

In this study, Both EFA and CFA do not target a generalization to a entire population because of constructing and establishing a theoretical model of measurement (DeVellis, 2017). The central aspect of this psychometric study will be quality and relevance of data and not necessarily representativeness. The constructs tested such as order timeliness, delivery completeness, responsiveness, and technology use are highly technical and contextual and hence was significant that the respondents selected were qualified to measure such attributes of logistics in the proper way. Also, the sampling method is best performed in cases where the researcher wants to uncover the intricate phenomenon using the key informants (Etikan et al., 2016). The logistics managers, retail supervisors, store owners and logistics professionals are selected strategically in this case since they are directly involved in the logistics decision-making and operations.

Data Collection Procedure is provided in Figure 1 and presents the procedural model of the EFA-CFA applied in the paper. The figure shows a three-step procedure of the development and validation of the Logistics Perfect Order (LPO) Measurement Model based on a methodological Exploratory Factor Analysis (EFA) - Confirmatory Factor Analysis (CFA) technique. The arrows follow the directional flow with feedback loops, which is also in line with the literature on scale-development and psychometric validation that underlines that the construction of measurement is a cyclic process and not strictly linear (DeVellis, 2017; Boateng et al., 2018; Hair et al., 2019).

Figure 1

EFA-CFA Procedural Model



Phase 1 is the theoretical background and instrument development. Phase 1 determines the conceptual and qualitative base of the instrument. The constructs of the Theory Guide are based on the known logistics, service quality, and supply chain performance theories. Scientifically-based item generation is highly suggested in the development of measurements to avoid the under-representation of constructs and maximize content validity (DeVellis, 2017; Netemeyer et al., 2003).

To add to the theory is the In-Depth Interviews (IDIs) that offers contextual and practitioner-based information that reflects operational realities that are mainly not represented by purely theoretical models. Qualitative exploration aligns with mixed-method and pragmatic research paradigms that recommend the use of triangulation between the literature and the field experience to enhance construct relevance (Creswell & Poth, 2018; Saunders et al., 2019).

Theory and IDIs outputs are merged in the Survey Questionnaire (SQ) Design where the items are worded, scaled and designed to capture both the academic aspects and the operational peculiarities of the local context. The instrument is then subjected to Expert validation and Reliability Testing, which was done by the panel reviewer and subsequently the pilot study Cronbachs alpha tests.

Phase 2 is the quantitative exploratory analysis and model generation. Phase 2 changes to empirical structure discovery. After the data collection, the dataset is submitted to EFA in order to determine the latent factor structures behind the variables observed. EFA was used in cases similar to this study when the theoretical constructs have to be confirmed empirically or when the dimensionality of the domain is not well-defined (Hair et al., 2019; Tabachnick & Fidell, 2019).

Immediately the model structure is developed, the EFA purification step entails the removal of weak or cross-loading or redundant items using statistical measurement criteria as the factor loading ($\geq$ 0.50) and the communalities. This procedure enhances scale parsimony and construct clarity, which are psychometrically advised, which is an iterative item reduction (Worthington & Whittaker, 2006; Hair et al., 2019). The deliverable of this phase is the model generation where domains of empirically supported LPO are produced. This step realizes the idea that the discovery of constructs should come before the confirmation and the structure of measurement must be able to mirror real data trends instead of being solely based on theoretical beliefs (Fabrigar et al., 1999; DeVellis, 2017).

Phase 3 is the confirmatory validation and model confirmation. Phase 3 is concerned with structural confirmation and validation of measurement. The collection of a separate or independent dataset is made in CFA data collection to minimize common-method bias and sample dependency that is highly encouraged in a scale validation study (Hair et al., 2019; Kline, 2016). Confirmatory Factor Analysis (CFA) is then adopted to test the hypothesized factor structure based on Phase 2. This step considers Goodness-of-Fit Indices which include CFI, TLI, RMSEA, SRMR, and Chi square/df ratios, as well as the measures of Validity and Reliability including Composite Reliability (CR), Average Variance Extracted (AVE), convergent and discriminant validity. The CFA offers the statistical data that the data at hand can be described by the offered measurement model and that constructs are internally reliable and unique to each other (Kline, 2016; Byrne, 2016; Hair et al., 2019).

The last step is the model confirmation of the LPO measurement structure indicating that the study results has attained satisfactory levels of construct validity, reliability, and external applicability. The feedback arrows in the framework also recognize that indices of modification or consideration of theory may require refinement but such refinements must be theory-based as opposed to being data-driven to prevent overfitting (Kline, 2016; MacCallum et al., 1992).

Data Analysis. The descriptive statistics, namely mean and standard deviation was utilized to summarize the demographic data of the respondents and obtain an overview of how they perceived the various logistics performance indicators. The average was used to capture the central tendency of the responses whereas the standard deviation was used to indicate the variability or dispersion about the mean. The measures gave information about the consistency of respondents experience and opinion on the main constructs that include timeliness and accuracy, order completeness and flexibility, product condition and satisfaction, delivery responsiveness and convenience, and technology integration. This will be in line with the recommendation of Creswell and Creswell (2018), who focus on descriptive statistics to summarize quantitative survey data.

The EFA was utilized to identify and examine the underlying latent structure of the measured variables using Principal Axis Factoring with appropriate factor rotation. Principal Axis Factoring (PAF) is an EFA factor extraction method. This study utlized registered SPSS (version 25). It deals with detection of latent variables (factors) that causes the shared (common) variance between observed variables. In the framework development, the authors Taherdoost (2019); Boateng et al. (2018); Brown (2018); Watkins (2018); Hesse-Biber (2020); and Castillo and Lo (2021) suggested the use of the principal axis factoring. There are many reasons why the PAF is a beneficial tool such as the focus on common variance which is suitable when factor analysis is intended to reveal latent constructs. It is also useful because it has the nature of providing more accuracy on theoretical constructs. The PAF is better suited to the objectives of EFA because its purpose is to provide a model of latent factors (unobserved variables), which is the purpose of EFA as opposed to PCA. Lastly, it is applicable also when normality is sometimes violated. PAF also remains strong where the data are not well-normally distributed, which is typical of the Likert-scale survey data in the real world.

Oblique rotation was used as the rotation process which is attributed to its preference based on theoretical as well as practical results of recent research. The selected factor correlates with the aid of oblique rotation specifically Promax, which is more realistic in the behavioral, social, and health sciences. This is because the human traits, behaviors and perceptions (such as trust, satisfaction, usability or anxiety) are hardly entirely independent. Most constructs in psychology and social sciences should correlate, and oblique rotations give more meaningful and valid factor structures (Watkins, 2018) .

Moreover, oblique rotation is applied because orthogonal rotation like Varimax makes the factors uncorrelated and this could have deceptive value of the data set and give wrong theoretical implications (Brown, 2018). Another important information emerging in the article by the authors was that the selection of orthogonal rotation when correlated factors are present may corrupt the actual factor structure and invalidate the theoretical validity of the model. Also, Oblique rotation is used to enhance factor loadings and interpretability (Boateng et al., 2018). Oblique models tend to produce cleaner and more meaningful solutions to factors, particularly when variables tend to load onto more than one construct of interest.

The EFA facilitated a high number of items to important latent constructs depending on inter-item associations. Sample adequacy Kaiser-Meyer-Olkin (KMO) measure was used to assess the appropriateness of data to the factor analysis and Bartlett Test of Sphericity was used to test data appropriateness. It was a factor loading of ≥ 0.50 and eigenvalues greater than or equal to 1.0 following Kaiser's criterion (Kaiser, 1974). It served as the criteria to retain the items (Hair et al., 2014). It is necessary to use EFA in this research to ascertain the construct validity, as well as to ascertain the best grouping of items that are related to the dimensions of LPO in the retail industry. Sampling adequacy is a vital parameter of the Kaiser-Meyer-Olkin (KMO) used to determine whether the data is suitable to use in EFA which is core to construct development or validation like LPO. To test various dimensions of LPO, as in the case of this study, every dimension will be gauged by a number of survey items. The KMO helped determine the suitability of the relationship between the items to help extract these dimensions using EFA before the underlying factors are coherent. The values of KMO are high in the study which means that the patterns of correlations between the items in the survey are compact and the factor analysis provided results in clear and strong components.

After the EFA, Confirmatory Factor Analysis (CFA) was performed with version 4 of SMART PLS namely Partial Least Squares (PLS) - SEM in order to verify the factor structure and measure of model fit.

RESULTS AND DISCUSSION

This section presents the results and discussion beginning with the Exploratory Factor Analysis (EFA), followed by the EFA purification stage, and the Confirmatory Factor Analysis (CFA) results. The conclusion and the recommendations followed based on the findings of the study.

Exploratory Factor Analysis

KMO and Bartlett's Test

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Table 1

KMO and Bartlett's Test of Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.94
Bartlett's Test of Sphericity	Approx. Chi-Square	67136
	Df	4005
	Sig.	0

In table 1, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy gave a value of 0.940, which is classified as a marvelous category (Kaiser, 1974). Such a high KMO value means that partial correlations between the items are insignificant and worthy of factor analysis. The correlation matrix, based on the KMO results further indicate, it is highly compact, meaning there is a strong shared variance among the variables.

This finding makes sense within the framework of the demographic profile of the study, namely, that of managerial and supervisory respondents, moderate-to-long staying time in the retail organization. The results align with the expectation of a demographic profile of the SMEs, omnichannel retailing, no dedicated logistics departments, and heavy reliance on third-party last-mile solutions in Davao City. The large KMO likewise suggests that the large variety of logistics, delivery, coordination and service recovery indicators represents shared experiential dimensions which ought to exist in an environment where the logistics functions are integrated into the operational functions and reviewed on a frequent basis such that the respondents would judge the performance in integrated outcome based concepts.

Similarly, the Bartletts Test of Sphericity yielded a Chi-Square of 67,135.694 with 4,005 degrees of freedom that is very significant (p =.000). This proves that the correlation matrix discussed in KMO is indeed not an identity matrix and the variables are in meaningful interrelationship with each other. This result underpins the idea that the logistics performance indicators do not act alone in the Davao City retail setting, rather, they act as interrelated practices influenced by the real-time coordination requirements, flexibility requirements, quality assurance requirements, and third-party delivery requirements.

The combined KMO and the Bartletts Test obtained with extremely high KMO (0.940) and statistically significant Bartletts Test gives a good empirical evidence that the data meet the statistical requirements of Exploratory Factor Analysis (EFA). These diagnostics, as they are presented in combination with the respondent demographics, allow continuing with the extraction of factors and the rotation of oblique (Principal Axis Factoring with Promax rotation) with a high level of confidence.

The correlation matrix appended on Appendix D shows the item clustering where there are a few strongly related latent dimensions, with a lesser number of items being weakly related. The patterns are aligned with the demographic and organizational characteristics of the respondents, who are mostly middle-aged (35-54 years old), managerially placed (store managers, operations managers, supervisors), employees of SME-sized companies, work in omnichannel retail operations, and do not have separate logistics functional departments; they strongly depend on third-party last-mile services in the city of Davao.

First, there is a strong cluster of real-time delay coordination, customer communication and service recovery. The correlation of Item 8 (real-time delay coordination) with Items 12 (route and traffic monitoring; r = .954), 42 (protective wrapping; r =.971), 48 (CRM logging; r =.951), and some other items (Items 55, 60, 64, 69, and

88; r ranges .95-.99) are very high. This high degree of inter-item coherence is indicative of the operational factuality of the Davao City retailers in that monthly performance review, outsourced last-mile delivery, and traffic- and weather-induced disruption demand that managers be more focus on real-time coordination and customer-facing responsiveness than on the formality of upstream planning. Since the majority of the respondents are in the operational decision-making processes, not in the specialization, logistics-related jobs, the items naturally merge into one single highly salient factor, which is the exception handling and customer communication.

Second, the clear and equally powerful cluster of operational flexibility and urgent order adaptation appears around item 25 (flexibility plan). This item is very much correlated with Items 34 (r = .913), 41 (r = .893), 46 (r = .898), 66 (r = .906), 67 (r =.899), and 70 (r =.911). This cluster indicates adaptive fulfillment behavior that is especially essential with SME-dominated, omnichannel retailers in the Davao City where logistics decisions are often made on the spot by store- or outlet-level managers. The high level of coherence of these items suggests that respondents do not perceive flexibility, rerouting, and urgent response as a standalone practice but as an integrated operation capacity that is required to bring about the perfect order results under a tight urban setting.

Third, a very strong cluster of handling, packaging, product protection and quality assurance is witnessed. The correlations of item 36 (careful handling) with Item 38 (temperature control; r =.912), Item 40 (packaging standards; r =.879), item 47 (service quality metrics; r =.939) and items 51 (r =.897), 52 (r =.915), and 53 (r =.949) are strong. This aspect concurs well with the respondent profile, where a high percentage of retail, convenience store, supermarket, and pharmacy managers are represented and, in this case, product condition on delivery is a customer satisfaction element, and it is also a compliance factor. These practices related to quality are closely connected in a city, where last-mile delivery is widely outsourced, and one evaluates the performance in terms of these aspects.

Conversely, a number of the early planning, forecasting and scheduling items (Items 1-7) exhibit quite low to moderate correlations with subsequent operational items (in many cases close to 0 to .30), with the exception of the high correlation between Item 3 and Item 7 (r =.773). This less integrated state is in line with the demographic result that more than 90 percent of companies do not have a specific logistics or supply chain department, which implies that formal planning and forecasting processes are not so ingrained in daily decisions making as real-time coordination and execution.

The correlation structure reveals that there are three or four major and practice-oriented dimensions that mainly contribute to the measurement model, like real-time coordination and service recovery that are based on CRM, operational flexibility and urgent response, handling and quality assurance, and a minor planning/technology scheduling sub-factor. This trend is conceptually and factual consistent with the demographic and organizational facts of the Davao City retail and last-mile logistics ecosystem, and offers a robust empirical basis to go ahead with Exploratory Factor Analysis (EFA) to formally extract and refine these latent constructs.

Dimensions that Define Logistics Perfect Order (LPO) in Retail

The communalities table provided on Appendix C presents the proportion of the variance in each indicator and explained by the extracted factors using the Principal Axis Factoring. Communalities, usimg the standard of ≥ .50 are generally considered strong and values between .30 and .49 are moderate and acceptable in several exploratory studies (Hair et al., 2019; Costello & Osborne, 2021).

The communalities exhibited strong (≥ .50) were observed in items such as flexibility and responsiveness measures (Items 28, 29), handling and product protection (Items 38, 39), service recovery and error prevention (Items 48, 51), and technology-enabled visibility and integration (Items 78–83, 88–89). The highest communalities were found in automated notification systems and tracking portals (Items 82 and 83), indicating that technology-enabled coordination and system integration are strongly represented in the extracted latent structure.

A substantial number of indicators fall within the moderate range (.30–.49), including warehouse management systems, barcode verification, packaging controls, complaint handling mechanisms, and ERP-enabled coordination. These items demonstrate acceptable shared variance and remain meaningful contributors to the latent constructs, particularly in domains related to operational control, handling integrity, service recovery, and digital integration.

However, several items exhibit low communalities (< .30), particularly those associated with basic operational planning and routine coordination practices (e.g., Items 3, 5, 6, 7, 8, 11, 25, 26, 32, 34, 43, 84). Low communalities suggest that these indicators contain higher unique variance and are not strongly explained by the common factors. In exploratory research, such values may signal that the item is either conceptually distinct, context-specific, or weakly aligned with the emergent factor structure (MacCallum et al., 1999).

Importantly, the overall Kaiser–Meyer–Olkin (KMO) value of .940 indicates excellent sampling adequacy (Kaiser, 1974), suggesting that despite some lower communalities, the correlation matrix remains highly factorable. In large-scale instrument development, retention of selected lower-communality items may be theoretically justified if they capture strategically important but context-specific aspects of logistics execution, particularly in emerging-market retail environments.

EFA Total Variance Explained

Table 2 on the Total Variance Explained showed that the first four factors extracted have significantly large eigenvalues than the other items, which implies

Table 2*Total Varaince Explained*

Factor	Initial Eigenvalues			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total
1	23.009	25.565	25.565	21.169
2	18.66	20.733	46.298	20.497
3	11.7	13	59.298	11.895
4	4.467	4.964	64.262	3.336
5	2.218	2.464	66.726	2.042
6	1.812	2.013	68.739	2.131
7	1.778	1.976	70.714	2.635
8	1.563	1.737	72.452	2.838
9	1.392	1.547	73.998	2.375
10	1.273	1.415	75.413	5.37
11	1.18	1.311	76.724	1.809
12	1.102	1.225	77.949	2.127
13	1.057	1.174	79.123	2.204
14	0.991	1.101	80.224	
15	0.969	1.077	81.301	

16	0.943	1.048	82.349	
17	0.905	1.006	83.355	
18	0.875	0.973	84.328	
19	0.843	0.936	85.264	
20	0.801	0.89	86.154	
21	0.759	0.843	86.997	
22	0.71	0.789	87.785	
23	0.65	0.722	88.507	
24	0.641	0.712	89.22	
25	0.588	0.653	89.873	
26	0.556	0.618	90.491	
27	0.537	0.597	91.087	
28	0.479	0.532	91.62	
29	0.466	0.518	92.138	
30	0.448	0.498	92.636	
31	0.409	0.455	93.09	
32	0.394	0.438	93.529	
33	0.371	0.412	93.94	
34	0.317	0.352	94.292	
35	0.305	0.339	94.631	
36	0.268	0.298	94.928	
37	0.254	0.282	95.211	
38	0.245	0.272	95.483	
39	0.23	0.256	95.739	
40	0.227	0.252	95.991	
41	0.207	0.23	96.221	
42	0.2	0.222	96.443	
43	0.187	0.207	96.65	
44	0.182	0.202	96.852	
45	0.167	0.185	97.038	
46	0.161	0.179	97.216	
47	0.155	0.172	97.388	
48	0.143	0.158	97.546	
49	0.139	0.154	97.701	

50	0.132	0.146	97.847	
51	0.126	0.14	97.987	
52	0.121	0.134	98.121	
53	0.111	0.124	98.245	
54	0.106	0.118	98.363	
55	0.098	0.109	98.471	
56	0.09	0.1	98.571	
57	0.085	0.094	98.665	
58	0.08	0.089	98.754	
59	0.076	0.085	98.839	
60	0.072	0.08	98.919	
61	0.07	0.078	98.998	
62	0.065	0.072	99.07	
63	0.063	0.07	99.139	
64	0.059	0.065	99.204	
65	0.055	0.061	99.265	
66	0.052	0.058	99.323	
67	0.051	0.056	99.38	
68	0.048	0.053	99.433	
69	0.047	0.052	99.485	
70	0.043	0.048	99.533	
71	0.041	0.046	99.579	
72	0.036	0.04	99.618	
73	0.035	0.038	99.657	
74	0.033	0.037	99.694	
75	0.031	0.034	99.728	
76	0.029	0.032	99.76	
77	0.028	0.031	99.791	
78	0.023	0.026	99.817	
79	0.023	0.025	99.842	
80	0.021	0.023	99.865	
81	0.019	0.021	99.886	
82	0.016	0.018	99.904	
83	0.016	0.018	99.922	

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84	0.015	0.017	99.939	
85	0.014	0.016	99.955	
86	0.013	0.014	99.969	
87	0.012	0.013	99.982	
88	0.009	0.01	99.991	
89	0.005	0.005	99.996	
90	0.003	0.004	100	

Extraction Method: Principal Access Factoring

Rotation: Pronax, oblique rotation

that they capture the most significant structure within the dataset. In Factor 1 alone, it explains a total variance of 25.565 percent followed by a total of 20.733, 13.000, and 4.964 percent in Factor 2, Factor 3, and Factor 4 respectively which gives a cumulative variance of 64.262. When conducting multivariate research of behavior and management, 50 to 60 percent cumulative variance is already held to be acceptable, and anything exceeding 60 percent is said to be a significant indication of dimensional adequacy (Hair et al., 2019; Tabachnick & Fidell, 2019). The rapid decrease in eigenvalues beyond the fourth factor is an indication of a natural break whereby extra factors do not add much explanatory value. This tendency is consistent with the theoretical assumption that a measurement instrument will be modeled as a few (dominant) latent domains, as opposed to a huge number of discontinuous elements.

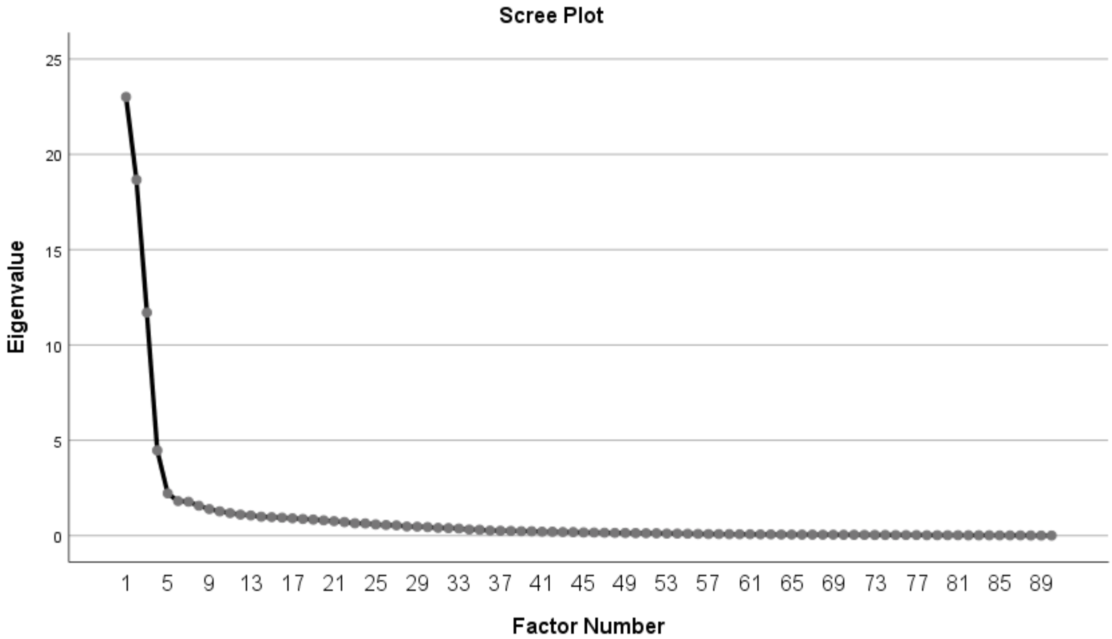
Even though the factors 5 to 13 each yielded eigenvalues surpassing a one, the use of the Kaiser Criterion is highly denounced in methodological literature. The eigenvalue-greater-than-one rule was first offered as a heuristic rule by Kaiser (1974). However, later empirical work found the rule easily results in over-extraction especially when the number of variables is large, such as instruments with more than 40 or more items. The evidence of simulation provided by Zwick and Velicer (1986) demonstrated that Kaiser rule has a tendency to increase the number of factors whereas researchers have warned against its application as the only retention technique. It is a statistical fact that in large item pools, like the current 90-item matrix, multiple small items have a statistically significant eigenvalue of more than one even in the case when they are not a meaningful construct. Therefore, the fact that there are thirteen eigenvalues greater than a unit does not necessarily comfort the case of keeping thirteen theoretical dimensions.

Factor 1 (25.57) is the dominant factor which can explain 64.26% of the overall variance, and it is followed by Factor 2 (20.73) and Factor 3 (13.00), and Factor 4 (4.96). This shape of concentration of variances resembles closely the scree plot which has a sharp drop in the eigenvalues till the fourth factor and a distinct elbow beyond that point. The trend of the four factors indicate the demographic representation of the respondents in the sense that they are mostly middle-aged managers and supervisors with moderate to long organization tenure, working in SME-dominated, omnichannel retailing companies that do not have dedicated logistics units and rely on third-party last-mile services. In these environments, fundamental issues of operation, like instantaneous coordination and communication with customers, operation adaptability, product quality and product management, and technology-based control systems become the most conspicuous and common dimensions of logistics perfect order performance.

Moreover, the concept of parsimony is very favourable to the four-factor solution. Parsimony claims to support the fewest factors that will be able to clarify the observed correlations with an adequate degree of conceptual clarity and statistical adequacy. Both Kline (2016) and Fabrigar et al. (1999) assert that in many cases complex factor solutions result in cross-loadings, unreliable estimates and ineffective replication in subsequent Confirmatory Factor Analysis (CFA) or Structural Equation Modeling (SEM). In comparison, a parsimonious factor model is easier to interpret, more theoretically consistent, and more stable. This conclusion is also supported by the rotated sums of squared loadings, and the reason is that the first four factors still have substantial explanatory content after rotation, but the subsequent factors have inconsistent or insignificant contributions. Together with convergence of the variance magnitude and the logic of scree, methodological caution of the presence of eigenvalue inflation and the parsimony principle, it is carried out that four major latent domains will be retained as the most statistically valid and theoretically significant display of the structure of the data.

Figure 2

Scree Plot



This prevailing position of the initial factors is theoretically aligned to the research in logistics and service quality, which highlights that capabilities at the execution level, including real-time coordination, delivery flexibility, handling integrity, and service recovery, is likely to induce the most amount of perceived logistics performance variance (Bowersox et al., 2016; Mentzer et al., 1999; Christopher, 2016). This pattern becomes substantively significant when considered through the prism of the demographic of the sample participants, who are mostly middle-aged managers and supervisors, and work in SME-based, omnichannel retail organizations in Davao City with limited formal logistics systems and relying heavily on third-party end-of-the-road services. In these situations, it is natural to have a focus on the performance perceptions around the more evident day-to-day execution and customer-facing activities that explain the prominence of the first few factors in the variance structure.

Further, the eigenvalues decrease more slowly, and make a relatively flat scree, meaning that further factors bring additional but more relatively smaller degrees of explained variance. Although Cattell (1966) warns that these later components are most accurately regarded as noise, current factor analysis sources indicate that these factors in many cases represent situational or supportive factors instead of constructs (Fabrigar & Wegener, 2012; Costello & Osborne, 2021). This connotation is consistent with the results of this research, in which later determinants denote the aspects of planning, infrastructure, technology assimilation, and coordination-related subtleties that are significant yet less influential in forming the perceptions of the overall logistics performance among the Davao City retailers. The scree plot together with the Kaiser criterion (eigenvalues>1) and high levels of theoretical consistency, the scree plot best justifies the retention of 4 factors and at the same time highlights the centrality of the early execution-based dimensions. The combined evidence offers a more balanced foundation of including factors (Hair et al., 2019; MacCallum et al., 1999).

Item Indicators that Describes LPO Dimensions

Table 3 displays the 4-factor solution obtained in the exploratory factor analysis, where the distribution of logistics perfect order performance items is

Table 3:*Distribution of SQ Items Across the 4 Extracted Factor-Solution*

Factor	Underlying Dimension (Suggested Label)	Question Numbers	No. of Items
Factor 1	Product Quality Assurance & Service Recovery	36, 38, 40, 44, 46, 48, 49, 50, 51, 52, 55, 56, 57, 62, 64, 70, 71, 75, 77, 78, 82, 84, 89, 90	24
Factor 2	Delivery Flexibility, Communication & Customer Coordination	25, 34, 39, 41, 45, 53, 58, 60, 61, 65, 66, 67, 69, 72, 73, 74, 76, 79, 80, 83, 85, 88	22
Factor 3	Customer Relationship Management & Packaging / Handling Controls	8, 12, 16, 22, 42, 43, 47, 54, 59, 63, 68, 81, 87	13
Factor 4	Route Planning, Forecasting & Operational Reliability	2, 13, 14, 23, 24	5

Extraction Method: Principal Axis Factoring

Rotation: Oblique (Promax)

demonstrated in the evidently interpretable latent dimensions. The Principal Axis Factoring with Promax (oblique) rotation EFA resulted in a four-factor structure, which represents theoretically consistent and operationally significant logistics execution and customer-oriented fulfillment domains. The application of an oblique rotation is suitable when considering behavioral and operations management studies owing to the fact that, underlying constructs are seldom independent, but they are rather likely to correlate in a real organizational environment (Fabrigar et al., 1999; Tabachnick & Fidell, 2019).

The derived factor groupings exhibit conceptual convergence, statistical power, and practical interpretability, which are three major measurements suggested in scale development and construct validation texts (Hair et al., 2019; Brown, 2015). The factor structure is founded under the pattern structure where most of the data falls above.50 and very few of.40 -.50 which is not considered bad as per various literatures.

Factor 1 Product Quality Assurance and Service Recovery (24 Items) is the most powerful domain. It included the items concerning the control of the product condition, prevention of defects, returns management, compliance with complaints resolution, service quality indicators, and post-technology monitoring. The close proximity of the items like careful handling, temperature control, packaging standards, zero-error delivery, speed in complaint resolution, and integration of systems reflects the high level of orientation towards end-to-end quality governance and corrective systems after delivery. In conceptual terms, this aspect coincides with the view of Bowersox et al. (2013) and Christopher (2016), who suggested that accuracy of orders, condition upon delivery, and responsiveness to failures are vital to the performance pillars.

The use of service recovery measures to include the high response of issues, replacement/refund policies, and CRM-based logging indicates the service quality tradition represented in marketing, as well as operations literature. Responsiveness and assurance plays a large role in customer satisfaction and loyalty especially in the event of service failures (Zeithaml et al., 1988). On the same note, recovery effectiveness is in most cases, a more significant determinant of perceived service quality than error-free delivery itself (Grönroos, 2007). The technological elements of this factor (system integration, dashboards, tracking) also resonate with the current evidence of the significance of digital infrastructure in increasing the visibility of quality and eliminating variability between the processes (Nguyen et al., 2021). In general, Factor 1 is a comprehensive quality-management and corrective-response atmosphere, of preventive and restorative aspects of logistics performance.

Factor 2 Delivery Flexibility, Communication and Customer Coordination (22 Items) groupings include items that explain adaptive delivery scheduling, multi channel communications, ERP/GPS based coordination, and responsiveness to urgent or exceptional demands. This dimension emphasizes the ability of the organization to dynamically match the operations of delivery to the changing customer demands and environmental conditions. Availability of SMS/email messages, electronic payments, real-time tracking, and routing flexibility signify the combination of the notion of omnichannel communication and operational agility, which the modern supply chain strategy literature discusses intensively (Chopra and Meindl, 2023; Hubner et al., 2016).

Theoretically, this aspect is in accordance with the flexibility and responsiveness dimensions of logistics capabilities models. As Christopher (2016) and Mentzer et al. (2001) contend, the customer-centric logistics performance is the characterization of service delivery and cost-efficiency. The items are also characterized by high communication, which is similar to the relationship marketing perspective, in which the high level of the exchange of information builds trust and satisfaction (Morgan & Hunt, 1994). In addition, the technological orientation, ERP systems, digital proof of delivery, automated notifications, displays how digital transformation works as an enabler of both coordination and visibility, which are the main themes in technology-enabled logistics performance models (Nguyen et al., 2021). Factor 2 can therefore be understood as the adaptation, customer interface in the operational execution and customer interaction, which focuses on responsiveness, transparency, and real-time interconnectedness.

Factor 3 Customer Relationship Management / Handling Controls (13 Items) combines the aspects of customer relation systems, package integrity, handling procedures and infrastructure support which establishes the domain of relational management and the physical protection of products. Co-loading of CRM recording, account-handling functions, complaint pathways, protective wrapping and FEFO inventory habits imply that the component encompasses both interactional governance as well as actual product protection. These two dimensions tend to be mutually reinforcing in the field of logistics and service management research. It hastens successful customer relationship management which is not just an issue of communication systems but also the relative physical reliability of provided products (Buttle & Maklan, 2019).

The components of the packaging and handling are related to the condition dimension of perfect order metrics that Bowersox et al. (2013) define as a major factor that defines supply chain performance. In the meantime, the CRM-related items indicate the customer management and adaptation theory by Ahmad and Buttle (1999), according to the authors, long-term relationships are reinforced by using regular feedback and personalized service process. The two-fold focus on relational systems and physical controls means that Factor 3 is the operational-relational nexus of logistics performance and makes sure that the quality of interaction with customers and product integrity are maintained simultaneously. This convergence is in line with integrated logistics-marketing systems that promote congruent information and material processes to attain sustainable competitive advantage (Esper et al., 2019).

Factor 4 Route Planning, Forecasting and Operational Reliability (5 Items) is less item-based but it represents a strategic and planning-related aspect that entails a concept of route stability, demand forecasting, contingency planning, and replenishment alignment. The items focus on upstream planning choices as opposed to the downstream service recovery or communication efforts. This aspect is closely aligned with the planning and reliability pillars of the supply chain management theory, in which predictive analytics, route optimization and risk mitigation are considered the preconditions to the consistent delivery performance (Chopra & Meindl, 2023; Simchi-Levi et al., 2021).

The fact that the number of items is not as large does not take away its theoretical value. According to Fabrigar et al. (1999), items that have fewer factors can still be robust provided that they have conceptual coherence and high loadings. Factor 4, in this case, encompasses the structural framework of the logistics implementation, which is proactive operational design, but not reactive correction. The existence of it highlights the difference between the reliability of planning and the flexibility of execution as two parallel but analytically disaggregated concepts in the logistics capability models (Christopher, 2016). In turn, Factor 4 will act as the strategic base on which the more dynamic and customer-facing factors described above will be supported.

The four-factor solution is shown to exhibit a multi-layered solution of logistics performance, which cuts across preventive quality control, adaptive communication, relational-physical protection, and strategic planning dependability. The outcomes of the oblique rotation imply that these domains are interdependent and not independent, which is why the real-life logistics systems with planning, technology, customer interaction, and quality assurance working in harmony. This convergence is consistent with the modern integrated supply chain theories that focus on synchronization of information, material, and relational flows (Christopher, 2016; Chopra & Meindl, 2023). The factor structure thus not only gives empirical validity but also theoretical richness giving a comprehensive measurement model to assess the perfect order fulfilment in logistics and technology-supported service delivery in the retail and distribution setting.

A stronger interpretative foundation in EFA is provided by the Scree Test proposed by Cattell (1966) which puts emphasis on the visual examination of the eigenvalue distribution to identify the presence of the "elbow" or point of inflection. The significant decrease between Factor 4 and Factor 5 in this instance denotes the shift in substantive variance to statistical residue. According to Hair et al. (2019) and Brown (2015), the scree plot with theoretical interpretability gives a more defensible retention decision than mechanical cutoffs does. The first four factors dominate and the incremental variance of the additional components is about 1-2 percent above Factor 4, which implies that the extra items may be due to measurement error, slight item clustering, or chance variability.

Item Indicators that Describes LPO Dimensions

Factor Structure. Table 4 shows the Factor 1 structure, which is called Product Quality Assurance and Service Recovery that comprises 24 indicators that will sum the ability of the firm to deliver orders in the appropriate state, eliminate any defects, and react efficiently to service failures. Logistically speaking, this is an aspect that shows that a perfect order may not be restricted to speed (perfect order) but can also be realized when the orders are accurate, damage proof and mechanisms employed to solve issues have been facilitated (Bowersox et al., 2016; Christopher, 2016). The fact that handling, packaging, returns prevention, complaint resolution, and digital monitoring items are included would indicate that the respondents view quality as an end-to-end operational activity that includes the warehouse handling, in-transit protection, customer interfacing, and post-delivery recovery. This type of coherent clustering can be linked to best practice in the interpretation of EFA, where items are allocated to a factor when they share meaning and operational unity (Costello & Osborne, 2021; Watkins, 2018).

Factor 1 has a first set of items associated with integrity of a physical product and quality of its handling, such as attentive handling when loading/unloading (Q36), perishable temperature (Q38), compliance with the packaging standards (Q40), and utilization of cushioning and tamper-proof seals (Q44). These indicators are the condition facet of the quality of logistics services, as customers assess delivery based on whether it is received, rather than on whether it is delivered intact, safe, and usable, which is a fundamental decisive factor in perceived logistics reliability (Thai, 2013; Kilibarda et al., 2020). Packaging discipline and product protection are the key operational controls in the retail and last-mile settings, where the risk of damage rises because of the number of touchpoints involved and frequent handling (Christopher, 2016; Gol & Catay, 2019). In this way, these products make logical sense and form a subtheme of delivery condition assurance.

The second cluster of indicators focuses on the measurement of quality, constant control, and defect prevention, which is reflected in the setting of predetermined service quality standards (Q46), the rigidity of quality processes to reduce returns (Q49), and the fact that returns are the result of transport breakage, but not product defects (Q50). This is a performance-management conception of logistics whereby companies establish service norms, track variances and create systematic practices that maintain standard results-in rationality akin to performance measurement systems that convert strategy to operational goals (Kaplan & Norton, 2017). Service metrics like accuracy, timeliness, and condition are the most frequent service-related metrics used in logistics performance research studies as the basis or foundational dimensions of service quality and outcomes of service fulfillment (Thai, 2013; Mentzer et al. 1999). By including specific quality measures (Q46) to this factor, it becomes more robust in terms of its interpretation as a quality governance area as opposed to an area of operation.

Table 4: *Factor Structure (Factor 1)*

Factor	Factor Name	Question No.	Question Statement
Factor 1	Product Quality Assurance & Service Recovery	36	Handles products carefully during loading/unloading
		38	Maintains the product temperature by ensuring temperature control for perishable products such as food, beverages, and medicines
		40	Adheres to product packaging standards
		44	Provides cushion and tamper-proof seals
		46	Establishes pre-defined service quality metrics such as delivery accuracy, timeliness, and product condition upon arrival at customer's end
		48	Resolves complaints systematically and fast
		49	Adheres to strict quality processes resulting in minimal product returns
		50	Ensures returns happen only due to transportation breakages and not product-related quality defects

		51	Ensures zero instance of wrong items delivered
		52	Ensures expired products are not delivered to customers
		55	Uses customer hotlines to address product concerns
		56	Trains in-store staff, account managers, and call center agents to address product concerns
		57	Resolves customer issues promptly
		62	Establishes delivery flexibility by delivering customers' demands even during fortuitous events
		64	Employs agile operations during seasonal demand spikes (e.g., Christmas, summer, fiestas)
		70	Uses fleet tracking and GPS to track customer orders
		71	Uses mobile apps or websites to monitor delivery orders
		75	Uses delivery technology to improve timely delivery
		77	Uses delivery technology to optimize fleet usage
		78	Uses delivery technology to enhance delivery transparency
		82	Automates notifications and dashboards to update delivery orders
		84	Updates customers through SMS, email, and phone on status of orders
		89	Integrates sales and logistics systems to reduce order errors and miscommunication
		90	Connects sales and logistics systems seamlessly to enhance overall customer satisfaction

A third cluster of the Factor 1 is a strong reflection of the dimension of perfect-order accuracy and compliance such as making sure that there are no wrong items delivered (Q51) and making sure that there are no products that are out of date delivered (Q52). These products indicate correctness and compliance of order, the key attributes of the right item, right condition logic of perfect delivery of orders, which is regularly pointed out by the literature on supply chain and logistics management as the most important outcomes of the quality of the offered services (Bowersox et al., 2016; Chopra &

Meindl, 2018). Prevention of expiry-related errors is not only an operation problem in many retail supply chains (particularly food, beverage, and regulated or sensitive products) but is also a customer safety and reputational problem. This is the reason why the respondents can find that expiry control and wrong-item prevention is part of the same underlying factor that regulates product condition and minimization of returns.

Furthermore, factor 1 highlights service recovery and customer support mechanisms which are strong including resolving customer complaints in a systematic and quick fashion (Q48), customer hotline (Q55), training of staff and call center agents (Q56), and customer resolution (Q57). These items help highlight that quality assurance is completed with the ability to get back from service failure, which is being stressed in customer-centric logistics and service quality learning. According to Esper et al. (2019), logistics value can be the most effective when companies are proactive in determining customer expectations and responsive to problems that interrupt customer experience. Responsiveness and recovery processes influence the perception of reliability and satisfaction in the last-mile and retail service quality models, particularly in situations where there is a disruption in delivery (Gol & Catay, 2019; Jaiswal & Singh, 2020). The fact that frontline training and hotlines are included can be viewed as the indicator that the system of quality exists within the company, which is not only technical but also human and relational, which is why it is possible to interpret this factor as Product Quality Assurance and Service Recovery, but not as Quality Control.

Factor 1 goes beyond conventional handling and complaint resolution and includes the indicators of resilience and agility, including providing delivery even in case of fortuitous events (Q62) and using agile operations when the demand peaks in seasons (Q64). This is in line with pieces of literature on resilience that defines reliability as the capability to sustain or swiftly recycle operations amid disruption, demand variability, and environmental vagueness (Asamoah et al., 2021; Hosseini & Jalil, 2019). The customers can perceive the uniform quality of products and reliable service during the peak seasons or disruptions, in real sense, as the operational excellence and not as distinct competencies. The occurrence of resilience-related items within the same factor suggests that the respondents consider quality assurance as an ability that does not give way to stress-related situations, which correlates with the frameworks of supply chain resilience measurement developed in the context of a developing economy (Asamoah et al., 2021).

The technology-enabled monitoring, transparency, and integration, fleet tracking and GPS (Q70), mobile monitoring (Q71), using technology to improve timeliness (Q75), optimizing fleet use (Q77), enhancing transparency (Q78), automating notifications and dashboards (Q82), updating customers through multiple channels (Q84) integration between sales and logistics systems (Q89), and linking systems to enhance satisfaction (Q90) is indicative of the fact that this factor is rooted in a contemporary perspective on quality Digital technologies facilitate more visibility, fewer errors, and contribute to a quicker process of detection-and-correction, and this directly enhances quality assurance and service recovery (Nguyen et al., 2021). Besides, it is stated in the studies of omnichannel delivery that the integration of sales, warehouse, and logistics functions with the help of technology lessens the rate of miscommunication and failed fulfilment, enhancing customer experience (Hubner et al., 2016; Nguyen et al., 2021). Accordingly, even the technical objects that belong to the same factor are theoretically consistent: digital enablement is not a new construct in this case, but one of the important mechanisms through which quality norms are operationalized and recovery speed is increased.

This coherent clustering, methodologically, validates construct validity as Factor 1 does show content breadth (handling, quality metrics, compliance, recovery, technology), and yet still a single operational definition which is assuring the product and service quality prior, during, and after delivery. This is consistent with scale-development articles that the labels on factors need to be consistent with the overall conceptual theme of the items and indicate a meaningful latent capability and not a short operational task list (DeVellis, 2017; Worthington & Whittaker, 2006). The grouping is also consistent with the EFA best practices where interpretability and theoretical plausibility are key elements in addition to the strength of statistics loading (Costello & Osborne, 2021; Fabrigar & Wegener, 2012). In general, Table 4 proves that Product Quality Assurance & Service Recovery is a significant latent area that supports the last-mile logistics performance and involves the preventive quality control, customer-oriented recovery processes, and integration based on technology to maintain customer satisfaction and avoid fulfillment failures (Bowersox et al., 2016; Christopher, 2016; Esper et al., 2019).

Factor 2, Delivery Flexibility, Communication & Customer Coordination (Table 5), is a mix of 22 indicators that describe how well the organization can adjust the delivery operations, keep the information flow continuous, and align the logistics operations with the customer expectations. This aspect captures the dynamic and relational aspect of logistics performance- how firms react to variability, interact with stakeholders, and real-time coordination of operational resources. Flexibility and coordination are always identified as important logistic capabilities in the framework of supply chain management, which produce a direct positive impact on customer satisfaction and competitive advantage (Christopher, 2016; Chopra & Meindl, 2018). The fact that these items cluster into one factor implies that the respondents do not believe that adaptability, communication channels and system coordination are separate practices but rather interconnected components of one delivering capability.

Table 5: *Factor Structure (Factor 2)*

Factor	Factor Name	Question No.	Question Statement
Factor 2	Delivery Flexibility, Communication & Customer Coordination	25	Keeps flexibility plan for urgent needs efficiently
		34	Delivers customer orders in sequence based on fairness and efficiency
		39	Ensures maintaining correct product stacking to prevent damages
		41	Ensures clear product packaging labeling
		45	Cascades survey feedback to various channels (hotlines, account managers, store staff) on the results of customer surveys
		53	Puts in place a mechanism for immediate replacement or refund due to product defect returns
		58	Relies on effective personal communications through phones or text to address customer concerns
		60	Balances delivery efficiency with fixed delivery routes
		61	Adjusts deliveries on urgent demands depending on truck availability to establish flexibility
		65	Uses ERP, GPS, and tracking apps for real-time delivery updates

		66	Uses SMS, email, or manual calls for smaller retailers
		67	Keeps updated customer data such as telephone numbers and contact persons for delivery emergencies
		69	Uses reliable ERP systems such as SAP and Oracle to ensure visibility between production schedule, warehouse stocks, and customer orders
		72	Secures delivery through digital proof of delivery such as OTP, e-signature, or photo confirmation
		73	Provides timely updates regarding delivery changes or delays
		74	Provides digital payment system for online orders
		76	Uses delivery technology to enhance delivery accuracy
		79	Uses delivery technology to ensure delivery efficiency
		80	Trains staff on the use of technology and customer services to complement technology deployment
		83	Uses delivery tracking portals to communicate deliveries with customers
		85	Uses digital communication for easy tracking and management of delivery orders
		88	Segregates and links sales and logistics systems to align sales orders, warehouse availability, fleet availability, and delivery schedules

One of the most noticeable sub-themes of Factor 2 is operational flexibility and flexible schedules, which are embodied through items like maintaining flexibility plans when there is an urgent need (Q25), scheduling deliveries flexibly (Q61) and prioritizing efficiency and fixed routes (Q60). These items contain the logistics principle that efficiency is not enough in the fluctuating consumer markets, but organizations must find a balance between stability of paths and the ability to re-align the delivery plans in case of a rise in demand or disruption. With respect to modern logistics competitiveness, agility and responsiveness are core in the context of last-mile operations where speed and customization of the products are valued by the customers (Christopher, 2016). On the same note, Asamoah et al. (2021) noted that flexibility in operations is a supply chain resilience factor that enables firms to stay in operation despite uncertainty. The fact that these indicators are present implies that the respondents equate high logistics performance with the capacity to be able to adapt rapidly without having to compromise fairness and service consistency.

The second thematic cluster is on the intensity of communications and multi-channel customer interactions, such as, using personal calls and texts (Q58), SMS or email updates (Q66), receiving change of delivery notification in time (Q73), and having digital contact portals (Q83, Q85). These products coincide with the customer-centric logistics theory, which states the perceived value of logistic services rises as people are constantly educated and engaged in the delivery process (Esper et al., 2019). Communication transparency in the study of service quality and retail logistics has been demonstrated to minimize uncertainty, create trust, and enhance intentions to behave in a particular manner in the context of service providers (Thai, 2013; Jaiswal & Singh, 2020). The aspect consequently captures not just the technical aspect of the delivery implementation, but also the emotional aspect of delivery in which efficient information transfer has become a quality of service determinant in total. This overlapping of operation and relationship practices is congruent to integrated logistics-marketing approaches which promote aligned material and information flows (Mentzer et al., 1999).

Factor 2 also uses technology based coordination and visibility such as ERP and GPS tracking (Q65), trusted enterprise systems (Q69), digital proof of delivery (Q72), technologies of delivery precision (Q76). These products are the digital backbone that enables flexibility as well as communication. The modern direction of logistics studies underlines the fact that the digitalization of sales, warehouse, and transportation systems increases transparency and minimizes miscommunication and the real-time decision-making process (Kache & Seuring, 2016; Nguyen et al., 2021). The literature on omnichannel also shows that inventory information, fleet accessibilit, nd customer requests should be coordinated with technology to reduce the number of fulfillment errors and enhance responsiveness (Hubner et al., 2016; Nguyen et al., 2021). The consideration of staff training in the use of technology (Q80) supports the idea that any use of digital tools should be supported with human potential to achieve their performance benefits to the fullest.

Customer feedback and system linkage are also elements of this aspect as indicated in items like cascading survey feedback to other channels (Q45) and the isolation and connection of sales and logistics systems (Q88). These indicators demonstrate that the organization focuses on feedback loops and cross-functional integration, which are the key elements of continuous improvement and service alignment. The performance management school of thought by Kaplan and Norton (2017) highlights the fact that there should be feedback mechanisms and alignment of the system to convert strategic goals into operational action. Customer feedback capture and response has been proposed to be a determinant of long-term service excellence in the context of the logistics service quality measurement (Kilibarda et al., 2020; Rahman et al., 2021). In this way, this section of Factor 2 explains the way communication would be both outbound and inbound learning and internal synchronization.

Factor 2 has a high level of construct validity methodologically as items are grouped to form a logically homogeneous latent dimension of adaptability, transparency and coordination. According to the literature, scale development suggests that the factors must have a statistical loading strength, as well as conceptual coherence, in order to be interpreted meaningfully (DeVellis, 2017; Worthington & Whittaker, 2006). The fact that flexibility, communication, and coordination are united in a single factor is theoretically realistic since in real logistics systems these capabilities frequently work together which is necessary to adjust schedules using communication and it is impossible to have communication without integrated systems. In EFA, this convergence represents best-practice suggestions, as it focuses on interpretability and theoretical foundations and empirical loading patterns (Costello & Osborne, 2021; Fabrigar & Wegener, 2012).

Table 6 shows Factor 3 named Customer Relationship Management and Packaging / Handling Controls that combines 13 indicators. It presents the dual focus on relational control over customers and the physical protection of products during the processes of fulfillment. This aspect explains why logistics performance is not merely an operational or technical process but a relationship and protective process that guarantees client interaction as well as product integrity. The overlap between the customer relationship systems and the physical handling standards is becoming more and more accepted as a factor in customer satisfaction and retention in the long-term, in the contemporary studies of logistics, and in service quality (Mentzer et al., 1999; Thai, 2013). This factor composition indicates that the respondents view communication, account management, packaging discipline, and infrastructure readiness as complementary components of one underlying capability.

Table 6:*Factor Structure (Factor 3)*

Factor	Factor Name	Question No.	Question Statement
Factor 3	Customer Relationship Management & Packaging / Handling Controls	8	Communicates and coordinates with customers on delivery delays in real time
		12	Creates a route plan and traffic monitoring to ensure timely deliveries
		16	Coordinates with customers to facilitate flexible and convenient deliveries
		22	Pre-schedules delivery windows with big customer accounts
		42	Protects products through protective wrapping for fragile packages
		43	Implements First-Expiry-First-Out (FEFO)
		47	Ensures customer complaints are logged in a Customer Relationship Management (CRM) system
		54	Logs product returns related to quality and uses them for process improvement
		59	Large companies offer delivery flexibility for key customer accounts during urgent replenishments
		63	Implements truck maintenance to ensure truck availability
		68	Employs account managers and sales representatives as the main communication bridge between customer and company
		81	Provides necessary logistical infrastructure to complement technology deployment

		87	Coordinates sales and logistics systems to improve on-time delivery performance

One of the main sub-dimensions of this factoris the relationship management and communication governance in which real-time coordination on delivery delays (Q8), allowing flexible delivery through direct coordination (Q16), pre-scheduling of the delivery windows with key accounts (Q22), and use of account managers as bridges of communication (Q68) are present. These actions are consistent with the principles of relationship marketing and customer-centered logistics, which is based on a consistent interaction and a coordinated approach tailored to the customer, which is more likely to increase trust, satisfaction, and loyalty (Esper et al., 2019; Shang & Lu, 2012). The quality of logistics services in terms of proactive communication and account management minimize uncertainty and perceived reliability, especially in the business-to-business distribution environment where the quality of the delivery has a direct effect on whether operations will continue. This congruency of the relational management and the logistics execution is similar to the statements of Christopher (2016), who pointed out that customer integration is one of the foundating pillars of supply chain competitiveness.

Another sub-dimension is packaging integrity and handling controls, as indicated in items on protection wrapping of delicate packages (Q42) and introduction of the practice of First-Expiry-First-Out on inventory (Q43). These items indicate that physical protection of goods is an integral part of customer relationship management, because the condition of products on delivery has a direct effect on the customer regarding service quality. According to Bowersox et al. (2016) and Chopra and Meindl (2018), practices like good packaging controls and inventory rotation like FIFO or FEFO are critical operational activities that support LPO by ensuring products are delivered in the correct condition, free from damage, and within acceptable quality standards. Packaging, as well as handling controls, are also associated with responsiveness and reliability dimensions in logistics service quality measurement models to show how tangible product care and intangible service interaction processes come to represent a single performance image (Kilibarda et al., 2020).

Factor 3 also includes feedback management and process-improvement features, which are reflected in recording complaints with customers into CRM systems (Q47) and capturing product returns to make process improvements (Q54). These parameters denote that there is a learning-oriented logistics culture in which customer feedback is formally recorded and converted into operation improvements. Kaplan and Norton (2017) posit that performance systems need to have feedback loops to maintain strategic alignment, whereas Rahman et al. (2021) state that the quality of logistics services increases when companies institutionalize complaint management and return analytics. These items are present in the same factor, which means that respondents consider customer interaction as a result of the combination of communication and the structured learning and continuous improvement, a strategy that aligns with the concept of integrated logistics and marketing frameworks that place high value on customer insight as a driver of operational excellence (Esper et al., 2019).

Operational support and infrastructure preparedness is another sub-factor of factor 3 which is indicated by truck maintenance so that it is available (Q63), the supply of the logistical infrastructure to supplement the deployment of technology (Q81), and the coordination of sales and logistic systems to improve on-time performance (Q87). These items carry the relational and protective themes out to the field of organizational competence and integration of systems which implies that great management of customer relationship is supported by measurable operational assets and coordinated information systems. Digital integration and infrastructural adequacy have been demonstrated to have a positive impact on logistics visibility and effectiveness of coordination in e-commerce and omnichannel setting (Nguyen, de Leeuw, and Dullaert, 2021; Nguyen, Simkin, Canhoto, and Padmanabhan, 2021). The incorporation of these factors proves that the respondents consider infrastructure and system connectivity as facilitating factors in sustaining customer relationship and product integrity.

Methodologically, the consistency of Factor 3 is aligned with best practices in scale development and scale-based exploratory factor analysis, in which construct validity is enhanced when grouped items are important in terms of statistical loading and conceptual integration (DeVellis, 2017; Worthington & Whittaker, 2006). The integration of CRM efforts, packaging protection, infrastructure preparedness and system coordination is an indicator that the latent dimension refers to a hybrid relational-operational construct that is logistically feasible in customer interactions and product protection contexts in which they cannot be separated as an aspect of service delivery. EFA best-practice literature highlights the importance of defensible factor labeling to be based on interpretability and theoretical fit (Costello & Osborne, 2021; Fabrigar & Wegener, 2012), which is reflected in the thematic consistency of this factor.

Thus, table 6 on Customer Relationship Management & Packaging / Handling Controls is a latent capability that can be used to bridge the human, physical, and technological aspect of the logistics performance. It highlights that customer satisfaction has to be maintained and achieved through effective communication and account management. It also considers packaging standards, infrastructure support and integrated information systems. This multidimensional construct is in line with the modern logistics and service quality theories that promote congruent relational and operational approaches to secure sustainable performance and robustness of distribution networks (Christopher, 2016; Esper et al., 2019; Nguyen et al., 2021).

Table 7: *Factor Structure (Factor 4)*

Factor	Factor Name	Question No.	Question Statement
Factor 4	Route Planning, Forecasting & Operational Reliability	2	Ensures orders are delivered within 24–48 hours or based on scheduled day of delivery
		13	Monitors weather conditions and plans contingencies to support reliable delivery performance
		14	Uses accurate forecasting and inventory management to strengthen delivery accuracy
		23	Coordinates with customers to align replenishment cycles
		24	Maintains delivery fixed routes

Table 7 presents Factor 4 named Route Planning, Forecasting & Operational Reliability. It is the factor with least number of items which brings together five indicators that are combined to form the strategic and anticipatory foundation of logistics execution. Factors 1 to 3 are focused on quality control, communication, and relationship management, factor 4 is on upstream planning and predictive abilities that facilitate consistent performance of delivery. Planning accuracy and route discipline are broadly identified as a defining determinant of fulfilment reliability in the theory of supply chain and logistics because they determine the organisation of resources, schedules, and inventory flows prior to the actual delivery (Chopra & Meindl, 2018; Christopher, 2016).

One of the main themes in this factor is the timeliness and compliance with the schedule of delivery, which is embodied in the item delivered in 24-48 hours or on scheduled days (Q2). This measure is a traditional dimension of logistics performance of on time delivery that has been traditionally viewed as one of the main indices of service reliability and customer satisfaction (Bowersox et al., 2016; Mentzer et al., 1999). Timeliness, is the result of an execution to a great extent, a product of proper planning, optimization of routes, good inventory, and transportation resources coordination. In several studies, the time of delivery is an important factor with regards to the perceived quality of logistics services especially in retail and the last-mile context where delays directly affect customer operations and expectations (Thai, 2013). Thereby, Q2 is the observational result that sets the predictive and planning aspects expressed by rest of the items in this factor.

The second sub-dimension is risk anticipation and contingency planning that involves paying attention to weather conditions and contingency planning (Q13). This item indicates the resilience-based perspective of logistics reliability in which performance is maintained by its regular and efficient nature and also by its readiness to environmental and operational failures. According to Asamoah et al. (2021), proactive risk management and contingency planning contribute to supply chain resilience, particularly in the developing economies where the infrastructure fluctuates and climate conditions can affect the delivery process. In the same extent, Hosseini and Jalil (2019) observe that long-term performance stability is realized in systems of logistics that can anticipate and respond to disruptions. The fact that weather tracking and contingency planning is included in this factor hence points to the fact that respondents relate reliability to foresight, and not to sticking to a set timetable.

Forecasting accuracy and inventory alignment is another important sub-factor in Factor 4 indicated by the item on the use of correct forecasting and inventory management to reinforce delivery accuracy (Q14). Forecasting is the analytic process which connects the demands anticipations with supply provision, and helps organizations to distribute transport resources, stock levels in warehouses, and manpower effectively. Chopra and Meindl (2018) hold that precise demand forecasting is associated with less stockout and surplus inventory, which enhances cost-efficiency and reliability of delivery. Inventory accuracy has also been linked to order completeness and timeliness in logistics service quality frameworks, which are two dimensions that are the foundation of perfect order fulfillment (Bowersox et al., 2016; Kilibarda et al., 2020). Having this component in the factor highlights the fact that predictive analytics and inventory discipline are seen by the respondents as a condition precedent to good delivery performance, and not as an independent back-office activity.

The rest of the items of factor 4 which includes scheduling replenishment processes with customers (Q23) and ensuring stable delivery routes (Q24), indicate the structural coordination and fixed delivery paths as other pillars of reliability in processes. The matching of replenishment patterns provides the simultaneity of the demand pattern of customers and distribution schedules, which is discussed in the literature on customer-centric logistics as one of the ways to decrease uncertainty and increase the service continuity (Esper et al., 2019). Meanwhile, fixed route maintenance indicates the operational standardization, and it is associated with efficiency, predictability, and the lower variability of delivery performance (Christopher, 2016). These items together demonstrate that reliability is both a product of flexibility and logistics structural architecture and rigorous routing policies that offer an unchanging structure upon which day-to-day logistics is to be conducted.

The methodological perspective of the small but consistent size of Factor 4 is aligned with the EFA literatures that factors with less items may be conceptually sound provided they demonstrate a high level of conceptual unity and high loadings (Fabrigar & Wegener, 2012; Costello & Osborne, 2021). The literature on scale development also highlights that items measuring a particular latent capability, although with a small factor size, are more likely to assess construct validity in combination of items (DeVellis, 2017; Worthington & Whittaker, 2006). In this regard, the five items always converge to one theme as proactive planning and operational foresight, which explains the label of the factor and helps to render its interpretive consistency.

Therefore, table 7 shows that the Route Planning, Forecasting & Operational Reliability is the strategic planning center of the logistics performance model. It embraces the anticipatory, analytical and structural practices that allow organizations to perform consistently even when there is variability in the environment and demand. This aspect goes hand in hand with the developed theories of supply chains that have placed accuracy in planning, optimization of routes, and risk preparedness as the cornerstone of consistent fulfillment performance (Christopher, 2016; Asamoah et al., 2021). Factor 4 is the upstream capacity that supports and stabilizes the more customer facing and execution-related dimensions revealed in the previous factors, and is a complete and theoretically informed measurement framework of logistics performance.

Goodness of Fit for Factor Structure

The pre-EFA began with 90 items. In the EFA section, 26 items were removed. In the purification stage, a re-run of the 64 items was conducted to ensure robustness of the model. Another 6 items were further removed of items below .40 in the factor loadings. This indicates that there were 58 remaining itmes in the purification stage.

Table 8:*Purification Decision*

Item Number	Primary Loading	Secondary Loading	Difference	Decision
1	0.48	0.174	0.306	Keep
2	0.437	0.238	0.199	Keep
3	0.944	0.017	0.927	Keep
4	0.15	0.121	0.029	**Review / Remove**

Table 8 illustrates the outcome of the item-purification procedure that was done during the EFA with Principal Axis Factoring using Promax (oblique) rotation re-run, The four-factor structure comprises (1) Product Quality Assurance and Service Recovery, (2) Delivery Flexibility, Communication and Customer Coordination, (3) Customer Relationship Management and Packaging/Handling Controls, and (4) Route Planning, Forecasting and Operational Reliability. These decisions were made in accordance with the methodological suggestions of Hair et al. (2019) and Costello and Osborne (2021), who stated that the analysis of primary factor loading, secondary (cross-)-loading, and the magnitude of loading-differences based on the pattern matrix, which represents the specific contribution of a particular indicator after having considered inter-factor correlations, led to item retention decisions. Indicators were retained if they demonstrated primary loadings of ≥ .50, cross-loadings below .30, and a loading separation of at least .20 between the highest and next highest loading. These criteria ensure strong factor interpretability, minimal cross-factor contamination, and structural clarity in the emergent four-domain model. Many of the indicators had very high primary loading and huge loading gaps thus verifying their strong suitability as measures of their corresponding latent constructs in the four finalized factors.

By comparison, those items marked as either reviewed or removed had poor primary loadings (< .40), slight distinction between primary and secondary loadings, and poor discriminant of factors. These loading patterns are a sign that such an item fails to meaningfully capture one of the latent constructs and can cause statistical noise of construct clarity (Hair et al., 2019, and Fabrigar and Wegener, 2012). Although borderline items have been kept especially items on factor 4 as it can be explained theoretically even if it did not enhance the conceptual definitions. However, numerous items that are non-statistically significant were dropped and the EFA was re-estimated to obtain a stable, interpretable, and theoretically consistent four-factor solution.

The purification phase was characterized by a very disciplined, theoretically guided screening procedure that was both empirically rigorous and conceptually coherent. Items were selected using common principles of scale development with strong primary loadings, low cross-loading, tolerable communalities, and definite domain conceptual ownership (DeVellis, 2017; Hair et al., 2019). The Kaiser-Meyer-Olkin (KMO = 0.958) measure was a measure of marvellous sampling adequacy and the Bartlett Test of Sphericity (2,016, p = 82,610; 2) was used to check the sufficient inter-item correlations to extract the latent structure. After re-estimation with Principal Axis Factoring together with Promax rotation, the fine-tuned four-factor solution accounted 84.759% of total variance, which is significantly higher than traditional 50-60 percent standards in measurement in social sciences and thus, showed very good construct representation and structural stability. The scree plot with the fourth factor depicted a definite elbow supporting parsimony and preventing over-extraction (Cattell, 1966; Kline, 2016). Despite the fact that some of the items had communalities in the .20-.40 range, they were retained based on the theory and in-line with the methodological advice that allowed moderate communalities as they occur at the exploratory stages where conceptual relevance and loading sufficiency are found (Fabrigar & Wegener, 2012; Costello & Osborne, 2021). In general, the purification removed redundancy and statistical noise, and did not compromise the breadth of construct. In addition, it gave a parsimonious but comprehensive measurement structure that could be used in confirmatory factor analysis.

In theory, the purification established the instrument into four theoretically foundational macro-capabilities, which represented the joint Logistics Perfect Order (LPO) framework. Factor 1 (Product Quality Assurance and Service Recovery) is a dimension that operationalizes core Perfect Order Fulfillment and Logistics Service Quality dimensions namely accuracy, condition and recovery responsiveness (Bowersox et al., 2016; Mentzer et al., 1999; Thai, 2013). Factor 2 (Delivery Flexibility, Communication, and Customer Coordination) reflects

Definition of Terms

Table 9:*Operational Definition of Terms*

Construct	Operational Definition (Based on EFA Results)
Product Quality Assurance & Service Recovery (PQASR)	Product Quality Assurance & Service Recovery refers to the organization's capability to prevent delivery errors and product defects while promptly correcting service failures through structured recovery processes and technology-enabled monitoring. It encompasses practices such as careful handling, packaging integrity, temperature control for perishables, zero-error and zero-expiry delivery policies, complaint logging and resolution, refund or replacement mechanisms, staff training, and the use of digital tracking and integrated information systems. This construct reflects the preventive and corrective dimension of logistics performance, where consistent product condition and rapid service rectification jointly sustain customer trust and satisfaction.
Delivery Flexibility, Communication & Customer Coordination (DFCCC)	Delivery Flexibility, Communication & Customer Coordination denotes the firm's ability to adapt delivery schedules, routes, and fulfillment methods while maintaining continuous and multi-channel communication with customers and synchronized internal coordination. It includes urgent demand adjustments, real-time delivery updates, digital proof of delivery, customer data management, ERP-supported visibility, and the use of both personal and digital communication tools. This construct captures the adaptive and interactional dimension of last-mile

	logistics, emphasizing responsiveness, transparency, and alignment between customer expectations and operational execution.
Customer Relationship Management & Packaging / Handling Controls (CRMPH)	Customer Relationship Management & Packaging / Handling Controls represents the integrated practice of building long-term customer relationships while ensuring physical product protection and disciplined handling processes that preserve order integrity. It combines relational mechanisms, such as CRM systems, account managers, scheduled delivery windows, and feedback utilization, with tangible safeguarding activities including protective wrapping, FEFO inventory rotation, truck maintenance, and logistical infrastructure support. This construct reflects the trust-building and protection-oriented dimension of logistics, where customer satisfaction is shaped by both interpersonal engagement and the careful treatment of goods throughout the delivery cycle.
Route Planning, Forecasting & Operational Reliability (RPFOR)	Route Planning, Forecasting & Operational Reliability refers to the organization's anticipatory and structural logistics capability to design efficient delivery routes, forecast demand and inventory needs, monitor environmental contingencies, and maintain fixed scheduling discipline to ensure consistent and predictable performance. It encompasses delivery time commitments, weather-based contingency planning, replenishment cycle coordination, and route standardization. This construct captures the strategic and predictive backbone of logistics operations, emphasizing foresight, planning accuracy, and systemic stability as foundations for dependable service outcomes.

flexibility and interfunctional responsiveness in line with Supply Chain Flexibility and Customer-Centric Logistics views (Christopher, 2016; Chopra and Meindl, 2018; Esper et al., 2019). Factor 3 (Customer Relationship Management and Packaging/Handling Controls) introduces customer relationship governance with physical product-protection precautions and conforms service quality to handling integrity and online views (Nguyen et al., 2021; Kache et al., 2016). Factor 4 (Route Planning, Forecasting, and Operational Reliability), which also has a smaller portion of variation, is the structurally different anticipatory ability with the foundation in transportation planning, disciplined scheduling, and forecasting reliability (Chopra and Meindl, 2018; Christopher, 2016). Theoretically, its retention is explained by it being an upstream stabilizing domain, which does not overlap with the capabilities of execution and customer-facing. The fine-tuned four-factor framework together empowers convergent validity, construct purity, and makes the LPO measurement model execution-based, customer-based, flexible, resilient, and digitally empowered, thus, an excellent empirical basis to follow up with CFA, reliability testing, and structural modeling.

Confirmatory Factor Analysis

The validation of the refined measurement model that resulted after the exploratory factor analysis and the following item-purification process was performed with the help of Confirmatory Factor Analysis (CFA). Although Exploratory Factor Analysis (EFA) is theory-blind, and its objective is to identify possible latent-built factors, CFA is theory-blind, and its aim is to test whether a previously defined factor structure provides sufficient explanations about the observed data (Brown, 2015; Kline, 2016). The CFA was used in the current research to test the factorial validity, internal consistency reliability, convergent or construct validity, and the discriminant validity of the four factor Logistics Perfect Order (LPO) measurement model in order to ensure that the indicators that have been retained reflect the intended latent constructs with some meaning to the retail logistics context.

CFA Measurement Model

Figure 3:*CFA Initial Measurement Model*

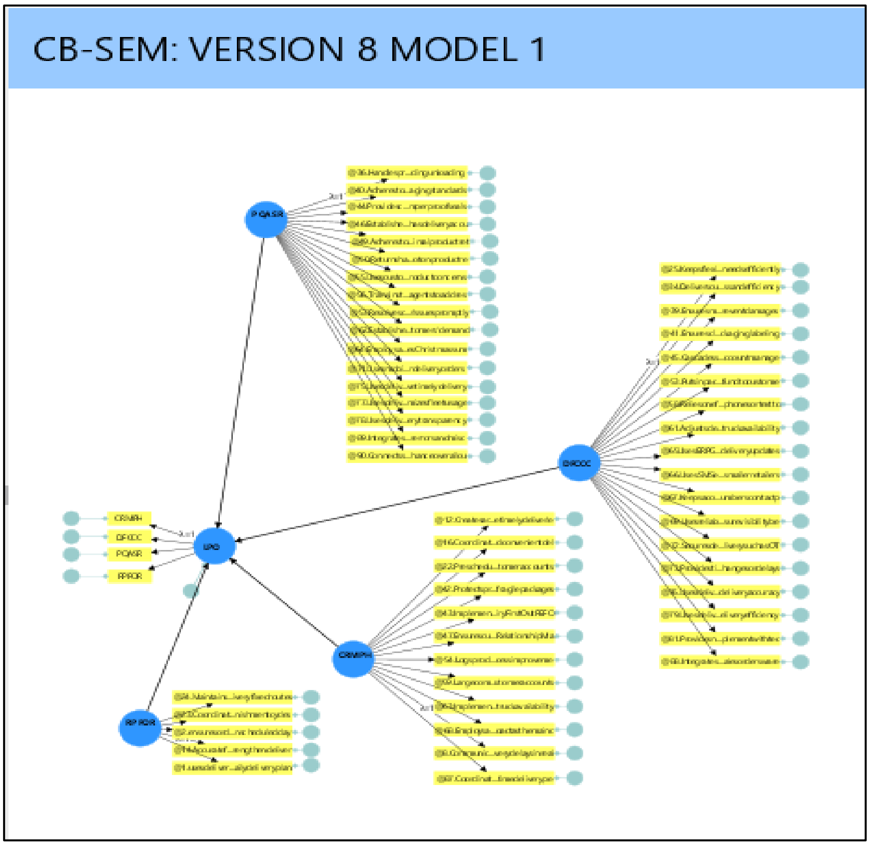


Figure 4 presents the revised Confirmatory Factor Analysis (CFA) measurement model specified to validate the purified four-factor structure derived from the Exploratory Factor Analysis (EFA). Following Principal Axis Factoring with Promax rotation, four empirically distinct yet theoretically interrelated latent constructs were retained and modeled as first-order reflective domains: (1) Product Quality Assurance and Service Recovery (PQASR), (2) Delivery Flexibility, Communication and Customer Coordination (DFCCC), (3) Customer Relationship Management and Packaging/Handling Controls (CRMPH), and (4) Route Planning, Forecasting and Operational Reliability (RPFOR). In accordance with confirmatory modeling principles (Hair et al., 2019; Kline, 2016; Brown, 2015), each observed indicator was restricted to load only on its designated latent construct, with cross-loadings constrained to zero. This specification reflects the transition from empirical exploration to theory-driven statistical validation, ensuring that the dimensional structure identified in EFA is not sample-dependent but supported by covariance-based model estimation.

Logistics Perfect Order (LPO) was subsequently operationalized as a second-order multidimensional construct reflected by the four purified first-order domains. The re-specification represents the outcome of rigorous item purification, where weak, redundant, or conceptually overlapping indicators were removed to enhance parsimony, internal consistency, and theoretical clarity, consistent with best practices in scale development (DeVellis, 2017; Boateng et al., 2018; Worthington & Whittaker, 2006). The higher-order modeling approach ensures comprehensive content coverage while preserving the multidimensional nature of logistics performance, recognizing that perfect order fulfillment emerges from the interaction of execution quality, coordinated flexibility, customer-interface stability, and predictive operational reliability.

The four domains correlation results reflects contemporary supply chain theory, which views logistics capabilities as mutually reinforcing rather than isolated silos (Christopher, 2016; Chopra & Meindl, 2018; Bowersox et al., 2016; Esper et al., 2019). In particular, PQASR captures execution integrity and recovery dominance; DFCCC reflects visibility and coordinated responsiveness; CRMPH operationalizes customer-facing handling and relational control stability; and RPFOR represents planning-based reliability and predictive stabilization. The revised CFA model therefore constitutes the validated confirmatory structure of LPO, serving as the empirical basis for evaluating model-fit indices, standardized loadings, composite reliability, convergent validity, and discriminant validity under structural equation modeling assumptions. As emphasized by Hair et al. (2019), Brown (2015), and Kline (2016), this confirmation stage is critical to establishing that the purified EFA-derived framework withstands theoretical scrutiny and covariance estimation requirements. Accordingly, the revised CFA model presents a theoretically grounded and empirically defensible representation of Logistics Perfect Order in the retail logistics context, integrating execution quality, coordinated flexibility, customer-interface control, and predictive operational reliability as interdependent pillars of sustained fulfillment excellence.

MEASUREMENTS

The parameter estimates indicated that the majority of measurement indicators significantly loaded on their respective latent constructs, with T-values exceeding the critical threshold of 1.96 and p-values below .05, thereby supporting convergent validity (Hair et al., 2019; Kline, 2016). Notably, indicators related to warehouse management systems and barcode verification exhibited strong statistical significance, reflecting robust measurement properties. However, several indicators such as capacity scalability and daily inventory checks yielded non-significant loadings, suggesting potential measurement weakness. Consistent with the recommendations of Byrne (2016), these items were evaluated further in conjunction with theoretical relevance and construct reliability metrics before decisions regarding retention or deletion were made.

CFA Factor Loadings

The measurement development process began with an initial pool of 90 items generated from IDI and literature synthesis, and theoretical anchors. Following established scale-development procedures (DeVellis, 2017; Boateng et al., 2018), the instrument was first subjected to Exploratory Factor Analysis (EFA) to examine dimensional structure and item performance. Guided by sampling adequacy diagnostics (KMO = 0.940, classified as "marvelous" by Kaiser, 1974) and Bartlett's test of sphericity, the EFA phase eliminated weak, cross-loading, and conceptually redundant indicators based on primary loading thresholds (≥ .50), loading separation criteria, and communalities, consistent with recommendations by Worthington and Whittaker (2006) and Hair et al. (2019). This purification reduced the instrument from 90 to 64 empirically supported items across emerging factor domains. Subsequently, the 64-item EFA-derived structure was advanced to Confirmatory Factor Analysis (CFA), where theory-driven specification and covariance-based estimation were applied (Kline, 2016; Brown, 2015). During CFA, further refinement was undertaken to improve model fit, internal consistency, and convergent validity, leading to the removal of statistically unstable or overlapping indicators. Through this sequential EFA–CFA validation process, the model was ultimately reduced to 29 statistically robust and theoretically coherent indicators, resulting in a parsimonious yet multidimensional representation of the final four-domain Logistics Perfect Order framework.

In the CFA stage, some outcome-oriented indicators were reassigned to load directly on the higher-order LPO construct rather than remaining within the four first-order domains. Empirically, these items, such as on-time delivery, zero wrong-item delivery, prevention of expired-product delivery, and predefined delivery-accuracy metrics, demonstrated stronger conceptual alignment as global performance outcomes that synthesize the effects of multiple operational capabilities rather than representing a single domain-specific behavior. In hierarchical component modeling, it is methodologically acceptable for a higher-order construct to include direct reflective indicators when those items capture the overarching performance dimension that integrates its subdomains (Hair et al., 2019; Kline, 2016; Brown, 2015). This is particularly appropriate when the higher-order construct is conceptualized as an outcome index rather than merely an abstract aggregation of capabilities. Moreover, within SmartPLS and variance-based structural modeling, a higher-order construct such as LPO must be specified with either first-order domains (repeated indicators approach or two-stage approach) or direct indicators to achieve identification; modeling LPO without associated domains or indicators would render the construct statistically undefined and theoretically incomplete (Becker et al., 2012; Hair et al., 2019). Therefore, reallocating selected global performance items to LPO ensured both theoretical clarity and methodological validity.

Table 10:*CFA Final Model Factor Loadings*

	CRMPH	DFCCC	LPO	PQASR	RPFOR
@12.Createsarouteplanandtrafficmonitoringtoensuretimelydeliverie	1				
@13.Monitorsweatherconditionandplansforcontingenciestosupportrel					1
@14.Accurateforecastingandinventorymanagementtostrengthendeliver					1.069
@2.ensuresordersaredeliveredwithin2448hoursorbasedonscheduledday			1		
@23.Coordinateswithcustomerstoalignreplenishmentcycles					0.462
@25.Keepsflexibilityplanforurgentneedsefficiently		1			
@36.Handlesproductscarefullyduringloadingunloading				1	
@40.Adherestoproductpackagingstandards				0.985	
@41.Ensuresclearproductpackaginglabeling		0.989			
@43.ImplementsFirstExpiryFirstOutFEFO	0.851				
@46.Establishespredefinedservicequalitymetricssuchasdeliveryaccu			4.292		

@47.EnsurescustomerscomplaintsareloggedinaCustomerRelationshipMa	0.992				
@49.Adherestostrictandqualityprocessresultinginminimalproductret				0.541	
@51.Ensureszeroinstanceofwrongitemsdelivered			4.1 84		
@52.Ensuresexpiredproductsarenotdeliveredtothecustomers			4.2 82		
@53.Putsinpaceamechanismforimmediatereplacementorrefundtocustome		1.014			
@54.Logsproductreturnsrelatedtoqualityandusedforprocessimproveme	0.99				
@55.Usescustomerhotlinestoaddressproductconcerns				0.958	
@57.Resolvescustomerissuespromptly				0.974	
@59.Largecompaniesofferdeliveryflexibilityforkeycustomeraccounts	1.008				
@62.Establishesdeliveryflexibilitybydeliveringcustomers’demand				0.994	
@63.Implementstruckmaintenancetoensuretruckavailability	1.024				
@65.UsesERPGPSandtrackingappsforrealtimedeliveryupdates		1.013			
@66.UsesSMSemailormanualcallsforsmallerretailers		1.024			
@73.Providestimelyupdatesregardingdeliverychangesordelays		1.022			
@75.Usesdeliverytechnologytoimprovetimelydelivery				0.991	
@76.Usesdeliverytechnologytoenhancedeliveryaccuracy		1.01			
@81.Providesnecessarylogisticalinfrastructuretocomplementwithtec	1.021				

@88.Integratesfullysalesandlogisticssystemstolinksaleso rdersware		1.048			

Table 10 presents the standardized factor loadings of the final CFA measurement model, providing evidence of indicator reliability and convergent validity across the four first-order constructs, Product Quality Assurance and Service Recovery (PQASR), Route Planning, Forecasting and Operational Reliability (RPFOR), Customer Relationship Management and Packaging/Handling Controls (CRMPH), Delivery Flexibility, Communication and Customer Coordination (DFCCC), as well as the higher-order Logistics Perfect Order (LPO) construct. In covariance-based SEM, standardized loadings ideally exceed 0.70, indicating that at least 49% of an indicator's variance is explained by its latent construct (Hair et al., 2019; Kline, 2016). The majority of retained indicators meet or substantially exceed this threshold, confirming strong indicator–construct relationships in the final validated model.

Within PQASR, high loadings are observed for adherence to packaging standards (0.985), customer hotlines (0.958), prompt issue resolution (0.974), delivery flexibility responsiveness (0.994), and delivery-technology support for timeliness (0.991). Although one indicator (strict quality process adherence, 0.541) demonstrates a moderate loading, it remains statistically acceptable and theoretically aligned with execution-control integrity (Worthington & Whittaker, 2006). These results confirm that PQASR captures a cohesive execution-quality and structured recovery capability.

For RPFOR, contingency planning (1.000) and accurate forecasting/inventory management (1.069) exhibit strong loadings, supporting the predictive reliability dimension of the construct. However, coordination of replenishment cycles (0.462) shows a comparatively lower loading, suggesting that planning-based coordination behaviors may be conceptually broader and less tightly unified than execution-driven constructs. Nevertheless, the retained items collectively support RPFOR as a predictive stabilization capability within the LPO architecture.

The CRMPH domain demonstrates consistently high loadings, including FEFO implementation (0.851), complaint logging systems (0.992), product return logging (0.990), truck maintenance (1.024), and infrastructure readiness (1.021). These magnitudes indicate strong convergence around customer-interface control and handling governance mechanisms, reinforcing CRMPH as an operational-control and relationship-stability capability.

Similarly, DFCCC shows very strong standardized loadings across flexibility and communication indicators, including flexibility planning (1.000), refund/replacement mechanisms (1.014), ERP/GPS tracking (1.013), SMS/email coordination (1.024), delivery-change notifications (1.022), delivery-accuracy technology (1.010), and sales–logistics system integration (1.048). These results indicate that digital visibility, coordinated communication, and structural flexibility are tightly integrated expressions of the DFCCC construct. Loadings exceeding 1.00 may occur in standardized solutions due to high inter-item correlations and do not necessarily indicate model misspecification, though they warrant cautious interpretation regarding potential indicator overlap (DeVellis, 2017).

At the higher-order level, the LPO construct demonstrates particularly strong associations with outcome-focused indicators such as on-time delivery (1.000), predefined delivery-accuracy metrics (4.292), zero wrong-item delivery (4.184), and prevention of expired-product delivery (4.282). These high coefficients emphasize that LPO is fundamentally anchored in accuracy, correctness, and product-condition integrity, consistent with Perfect Order Fulfillment theory (Bowersox et al. 2016). Large fixed loadings reflect scaling constraints used for model identification and are standard practice in SEM rather than estimation anomalies (Kline, 2016).

The final CFA model demonstrates strong indicator reliability and substantial convergent validity across constructs. Most indicators load highly and significantly on their intended latent variables, confirming the empirical robustness of the four-domain LPO framework. While several loadings approach or exceed unity, suggesting strong construct cohesion, the results collectively support the multidimensional yet highly integrated structure of Logistics Perfect Order, where execution integrity, predictive reliability, customer-interface control, and coordinated flexibility operate as interdependent pillars of fulfillment excellence.

Validity and Reliability of the Model in Assessing LPO

Cronbach's Alpha, Composite Reliability, and Convergent Validity. The values in Table 11 (Composite Reliability) suggest that the adjusted measurement model has acceptable to high levels of internal consistency and convergent validity, but one of the constructs (RPFOR) has a relatively low psychometric strength. Conventional thresholds in multivariate analysis and scale-development literature indicate that Cronbach's alpha and composite reliability (CR) should be at least 0.70, while Average Variance Extracted (AVE) should be 0.50 or higher to establish adequate convergent validity (Hair et al., 2019; DeVellis, 2017; Fornell & Larcker, 1981). A reliability coefficient of 0.70 or above suggests acceptable internal consistency among indicators, whereas an AVE of 0.50 indicates that the construct explains at least 50% of the variance of its indicators, confirming sufficient convergence of items on their intended latent variable. RPFOR is low, as there are very few items and many are moderate and weak but theoretically acceptable. Thus, it was retained.

Table 11: *CFA Composite Reliability*

	Cronbach's alpha (standardized)	Cronbach's alpha (unstandardized)	Composite reliability (rho_c)	Average variance extracted (AVE)
CRMPH	0.988	0.988	0.988	0.923
DFCCC	0.987	0.987	0.987	0.905
LPO	0.792	0.759	0.851	0.705
PQASR	0.961	0.962	0.965	0.796
RPFOR	0.647	0.619	0.65	0.426

In CRMPH (Customer Relationship Management & Packaging/Handling Controls) and DFCCC (Delivery Flexibility, Communication and Customer Coordination), the reliability indices are likewise quite high with Cronbachs alpha and composite reliability both 0.988 and 0.905 respectively and AVEs of 0.923 and 0.905. These statistics suggest that internal consistency is very high and shared variance is very large among indicators, which is an appropriate confirmation that items capture what they are supposed to measure. Nevertheless, methodological experts warn that coefficients near or higher than 0.95 also can be interpreted as a sign of either item redundancy or too much similarity in wording, not necessarily higher quality of measurement (DeVellis, 2017; Kline, 2016). Therefore, the constructs are highly reliable, but the size of these values indicates the possibility of the overlap between the concepts of certain indicators, which is typical of the operational and process-based scales of logistics.

The PQASR (Product Quality Assurance and Service Recovery) construct also has a high reliability and good convergent validity with the Cronbachs alpha of 0.961-0.962, composite reliability of 0.965, and AVE of 0.796. These findings support the fact that the indicators are consistent measures of the quality of assurance and recovery processes that are associated with the literature on logistics service quality quality that accentuates condition accuracy, complaint management, and recovery responsiveness as closely connected practices (Christopher, 2016; Mentzer et al., 1999). The fact that the AVE is well above the

0.50 mark is further evidence that the latent construct accounts for a large percentage of indicator variance, which supports the argument of convergent validity.

In addition, RPFOR (Route Planning, Forecasting and Operational Reliability) exhibits comparatively low reliability, with the Cronbachs alpha of 0.647 and 0.619, composite reliability of 0.650, and AVE of 0.426. These values are slightly lower than traditional values which means that its internal consistency and shared variance among indicators are weak. Although a few researchers do admit that exploratory or newly constructed constructs can afford alpha values of close to 0.60 (Worthington & Whittaker, 2006), the AVE of less than 0.50 indicates the lack of convergent validity by more rigid SEM standards (Fornell & Larcker, 1981). This trend implies that the RPFOR indicators might be conceptually heterogeneous or not homogeneous enough to justify the development of additional refinement, reduction of items, or even theoretical reason to maintain.

The LPO (Logistics Perfect Order) higher-order construct offers a satisfactory and desirable reliability profile with a Cronbach (standardized) and Cronbach (unstandardized) alpha of 0.792 and 0.759, composite reliability of 0.851 and AVE of 0.705. These values are within comfortable recommended ranges and are indicative of satisfactory internal consistency without redundancy. According to Hair et al. (2019), moderate but stable coefficients of reliability of second-order or outcome-oriented constructs are caused by its appropriateness in theory since they do not sacrifice the diversity of indicators, but their constructs remain coherent. The high convergent validity (AVE > 0.70) implies that the LPO construct is effective in the measurement of the common variance in its multi-dimensional indicators.

Therefore, the composite reliability findings depict a psychometrically sound measurement model, which is very strong with respect to customer-facing and coordination-oriented constructs, reasonable and theoretically relevant with respect to the higher-order LPO construct, and rather weak, yet interpretable, with respect to the planning-oriented RPFOR domain. This distribution reflects that the purification and confirmatory tests were effective in reducing error of measurement and maintaining conceptual coverage and thus passed accepted standards of SEM in internal consistency and convergent validity in applied logistics and supply chain research (Hair et al., 2019; DeVellis, 2017).

Discriminant Validity

The HTMT (Heterotrait-Monotrait Ratio) matrix was used to determine discriminant validity, in this case, the empirically distinct measurement of each of the latent constructs in the measurement model is evaluated. Discriminant validity is taken to be established when the values of HTMT are below 0.85 in a rigid criterion or 0.90 in a more relaxed criterion, showing that two constructs are not measuring the same conceptual domain (Henseler et al., 2015; Hair et al., 2019, Tan, 2025).

The values of the HTMT according to Table 16 vary between 0.042 and 0.199 with one pair standing at 0.85, most of them being significantly lower than the recommended cut-off levels. In general, this trend gives considerable statistical support to the assumption that constructs are rather empirically separable and independent in nature, and only one pair of constructs is close to the upper strict border.

Table 12*CFA Discriminant Validity*

	CRMPH	**DFCCC**	**LPO**	**PQASR**	**RPFOR**
CRMPH					
DFCCC	0.059				
LPO	0.054	0.086			
PQASR	0.042	0.078	0.85		
RPFOR	0.057	0.102	0.199	0.077	

Particularly, the HTMT values between CRMPH and DFCCC (0.059), between CRMPH and LPO (0.054), and between CRMPH and PQASR (0.042) show that there is little overlapping in construct, hence proving that customer relationship/packaging controls, delivery flexibility and coordination, and product quality/service recovery are distinct performance dimensions in logistics. Similarly, the relationships between DFCCC and LPO (0.086) and DFCCC and PQASR (0.078) are all well below the acceptable range, and thus, communication and coordination capabilities are empirically differentiated rather than overlapping constructs, despite the fact that they are operationally related to the outcomes of logistics and quality assurance.

The maximum value of HTMT is observed between PQASR and LPO (0.85), and that is not over the strict threshold. This is a high yet acceptable level of conceptual proximity, which is probably a natural theoretical connection between the quality assurance of products/service recovery and the overall logistic perfect order results. Although it is too near the boundary, it is not a formal violation of discriminant validity standards, but it portends conceptual relatedness and not measurement duplication. On the contrary, the correlations between the RPFOR, specifically RPFOR-CRMPH (0.057), RPFOR-DFCC (0.102), RPFOR-LPO (0.199), and RPFOR-PQASR (0.077) are all below the boundaries, supporting the opinion that route planning, forecasting, and operational reliability exist as a statistically independent planning-oriented construct distinct of customer-facing and quality-oriented constructs.

Methodologically, the fact that most of the HTMT ratios were lower indicates that the purification, item reassignment and construct re-specification steps were successful in eliminating redundancy and enhancing conceptual focus. In line with the suggestions of Fornell and Larcker (1981) and Henseler et al. (2015), high discriminant validity suggests that each of the latent variables would represent a distinct sphere of variance as opposed to measurement error. Pragmatically, the results suggest that CRMPH, DFCCC, LPO, PQASR, and RPFOR are discrete, but complementary dimensions in the Logistics Perfect Order. This apparent dichotomy increases the interpretability of the structural model and the plausibility of the hypothesis testing that follows since the observed inter-construct relationships can be viewed as theoretically relevant effects and not results of overlapping measurement.

Model Fit Indices

Table 13 presents the Model Fit Indices. It is possible to say that the estimated structural equation model shows good and significantly better overall fit to the observed data in comparison with the null (independence) model. The Chi-square of 1,312.026 with 373 degrees of freedom is significant (P =.001), as it should be due to the quite big size of the sample (N = 461). The Chi-square statistic used in the context of SEM is sensitive to large samples and complicated models and is often prone to rejecting a perfect fit even when the model is practically satisfactory (Kline, 2016; Byrne, 2016). Therefore, the importance is put on relative and approximate fit indices. The Chi-square/df ratio of 3.517 is quite comfortable within the traditional upper limit of 5.0, and is even within the more conservative range of 3-4, which is considered to be reasonable to good model fit, when compared to the null model ratio of 58.173, which is considered to be a model of extremely bad fit.

Table 13: *CFA Model Fit Indices*

	Estimated model	**Null model**
Chi-square	1312.026	23618.317
Number of model parameters	62	29

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Number of observations	461	n/a
Degrees of freedom	373	406
P value	0	0
ChiSqr/df	3.517	58.173
RMSEA	0.074	0.352
RMSEA LOW 90% CI	0.07	0.348
RMSEA HIGH 90% CI	0.078	0.356
GFI	0.836	n/a
AGFI	0.808	n/a
PGFI	0.717	n/a
SRMR	0.055	n/a
NFI	0.944	n/a
TLI	0.956	n/a
CFI	0.96	n/a
AIC	1436.026	n/a
BIC	1692.297	n/a

The measures of approximate fit further support the adequacy of the model. The Root Mean Square Error of Approximation (RMSEA) value of 0.074, with a 90% confidence interval ranging from 0.070 to 0.078, indicates a reasonable level of approximation error. According to conventional guidelines, RMSEA values below 0.08 reflect acceptable model fit, while values below 0.05 indicate close fit (Hair et al., 2019; Kline, 2016). The relatively narrow confidence interval suggests stability in the estimation and reinforces that the model demonstrates an acceptable, though not perfect, representation of the population covariance matrix. The general interpretation of RMSEA is that values lower than 0.08 are plausible and less than 0.05 is a close fit (Hair et al., 2019; Schumacker & Lomax, 2016).

The confidence interval is quite thin which indicates stability and accuracy in the estimate. Further, the Standardized Root Mean Square Residual (SRMR) value of 0.055 is sufficiently smaller than the 0.08 level, and it is determined that the average difference between observed and model-implied correlations is not high, and the model is effective in reproducing the empirical correlation matrix.

The incremental and the comparative fit indices perform well. The Comparative Fit Index (CFI = 0.960) and Tucker-Lewis Index (TLI = 0.956) are over the high thresholds of 0.95, which is the excellent comparative fit and indicates that the estimated model is a significant improvement over the null model (Hair et al., 2019; Kline, 2016). Equally, Normed Fit Index (NFI = 0.944) exceeds the standard 0.90 incremental fit. Absolute fit measures like Goodness-of-Fit Index (GPI = 0.836) and Adjusted GPI (AGPI = 0.808) are slightly less than the value of 0.90 which is the ideal but they are acceptable in applied behavioral research. Individuals generally agree that these indices are sensitive to the complexity of the model and large sets of indicators and thus should be viewed with care in current SEM practice

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(Byrne, 2016). The Parsimony GPI (PGPI = 0.717) means that there is a good balance of explanatory power and model simplicity and the refined model is thus efficient without the excessive use of parameters.

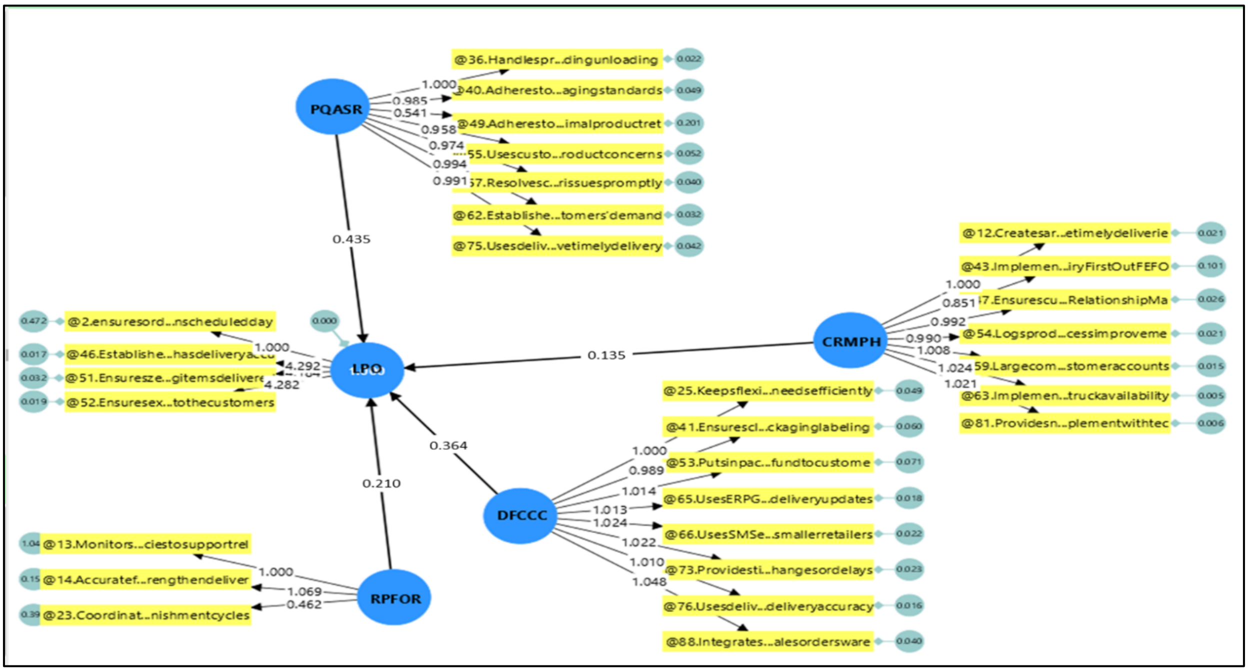
Lastly, the Akaike Information Criterion (AIC = 1,436.026) and Bayesian Information Criterion (BIC = 1,692.297) are relative fit statistics that can be used to compare the specifications of different models to compare them to the absolute goodness-of-fit (Kline, 2016). A decrease of these values would imply a better fit when competing models are compared.

The trend of the indices measured like acceptable Chi-square/df, reasonable RMSEA with close confidence limits, good SRMR, and great CFI/TLI/NFI, is reflection that the model that is estimated has a statistically sound and theoretically meaningful fit. This unanimity of evidence justifies moving forward to structural path interpretation and hypothesis testing and allows acknowledging a few refinements, in case of any, would be necessary, to further improve parsimony without compromising model validity.

Model Refinement

The confirmatory factor analysis (CFA) model in Figure 5 indicates a clarified and stingy structural-measurability designation of the Logistics Perfect Order (LPO) construct, with LPO being the central endogenous latent variable subject to four empirically authenticated operational capability sectors such as PQASR (Product Quality Assurance and Service Recovery), DFCCC (Delivery Flexibility, Communication and Customer Coordination), CRMPH (Customer Relationship Management and Packaging/Handling Controls), and RPFOR (Route Planning, Forecast This specification is not the previous large multi-construct model, but a theoretically integrated but statistically purified model, in line with SEM best-practices advice that puts an emphasis on parsimony, construct clarity, and empirical defensibility (Hair et al., 2019; Kline, 2016).

Figure 4 *Refined Logistics Perfect Order Retail Model*



The standardized loadings of the retained indicators of the four factors are very high with most indicating a load of over 0.70 which is the recommended level and some of them approaching one. These magnitudes show good indicator reliability and high convergent validity, which is in line with the standards proposed by Fornell and Larcker (1981) and DeVellis (2017).

The high outer loading of the PQASR domain is more specific, with the highest loadings of perfect order execution being the most observable and measurable (quality assurance, service recovery, and customer issue resolution). Equally, DFCCC measures, which include ERP use, tracking of delivery, digital proof of delivery and communication channels, represent the technological and coordination processes that put into practice last-mile responsiveness. CRMPH indicators reflect relationship management and packaging/handling controls whereas RPFOR indicators reflect the planning and forecasting functions of weather monitoring and replenishment alignment. All these domains make the multidimensional logic of perfect order fulfillment real as introduced in the logistics performance literature (Bowersox et al., 2016; Christopher, 2016).

At the structural level, the path coefficients imply that there are differences in the strengths of influence on LPO. The direct impact of PQASR is the strongest, which indicates that the integrity of the product condition, the speed of service recovery, and the prevention machinery of the error are the strongest empirical determinants of the perceived perfection of the logistics in the retail setting. DFCCC comes next as a modest predictor, with emphasis on the importance of communication infrastructure, digital visibility, and efficacy of coordination to predict the outcomes of delivery. CRMPH and RPFOR show smaller but positive effects, indicating that when compared to relationship management, packaging controls, planning, and forecasting, relationship management, packaging controls, planning and forecasting are enabling mechanisms, but rather supportive capabilities as opposed to a key indicator of perfect order outcomes. This top-down influence pattern echoes the views of dynamic capability theory which theorizes that operational performance is a result of the interplay between adaptive routines and executional responsiveness as opposed to the functions of planning (Teece, 2007; Eisenhardt & Martin, 2000).

The final model also reflects on the principle of the capability layering so common in the research of logistics and omnichannel fulfillment. Planning and forecasting (RPFOR) offer time/demand, relationship, and handling controls (CRMPH), customer interface stability, product integrity, real-time responsiveness, and digital visibility (DFCCC), and quality assurance with service recovery (PQASR) secure the end result of final delivery. All these capabilities come to a unified LPO construct, which is the holistic performance of fulfillment among retailers. This logical approach aligns with the research on last-mile and omnichannel logistics scholarship that view responsiveness, integration, and recovery as the real-world drivers of fulfillment excellence (Hubner et al., 2016; Lim et al., 2018; Esper et al., 2019).

The previous broad item specification has been replaced by the current narrow form with 29 items can not be taken to mean that this field has shrunk theoretically but rather made mature in terms of methodological development. The purification process eliminated weak, redundant or cross-loading indicators and then consolidated empirically overlapping constructs thus improving discriminant validity, reducing residual error, and improving global fit indices. This level of refinement can be considered in line with the classical doctrine of scale-development, where CFA is thought to be confirmatory and corrective in ensuring that indicators retained express their latent variables in a unique way and not semantically overlap (Nunnally, 1994; Byrne, 2016).

Lastly, the final model is a compromise between theoretical completeness and statistical parsimony. It embodies Logistics Perfect Order as multidimensional but execution-based construct with quality assurance and recovery mechanisms prevailing with the help of communication, coordination, planning and relationship controls. Instead of undermining the conceptual framework, the cutback presents the fundamental logistics competencies that empirically propel fulfillment excellence to a retail setting-a fact consistent with the resource-based, as well as capabilities-based, perspectives of the firm in its assertion that competitive performance comes as a result of bundled high-impact capabilities instead of multiple activities fragmented into small units (Barney, 1991; Teece, 2007).

Conclusion and Recommendation

Conclusion. Based on the successive application of the Exploratory Factor Analysis (EFA), indicator purification, and Confirmatory Factor Analysis

(CFA/CB-SEM), the research comes to a conclusion that the Logistics Perfect Order (LPO) fulfillment in the retail and last-mile setting is execution-oriented, capability-oriented, and integrative, as opposed to sole planning-based. The empirical findings continuously point to the effectiveness of product quality assurance and service recovery, delivery flexibility and communication coordination, customer-facing handling controls, and route planning with operational reliability to explain more variation in LPO performance than forecasting and pre-delivery planning. In actual sense, disciplinarily implemented in organizations at the time of delivery and in the post-delivery periods have more effective impacts on perfect order outcomes than that which the organizations simply plan.

The results also indicate that in the environment of uncertainty of delivery, the real-time coordination, quality assurance and service recovery has been working as one operational unit where monitoring, communication and corrective action cannot be separated. Flexibility is to be seen as an institutionalized system property, ingrained in routing policies, fleet structure, digital tracking practices and customer accommodation protocols, as opposed to an ad hoc response. Technology acts as a capability amplifier and makes visibility, speed of coordination and the control of accuracy visible, faster and more precise rather than replacing human judgment or procedural discipline. Feedback loops and complaint management are also empirically replaced with marginal post sales operations with core logistics control systems that maintain integrity of order and customer confidence. Similarly the sales-logistics integration is growing out of the mere coordination to information backbone that provides transparency and cross-channel recovery. Resilience is also reflected in the response to crisis, but also in the discipline of routine maintenance, infrastructure preparedness and seasonal responsiveness to be found in daily operations. In general, LPO is proven to be multidimensional in type and a single measure simplifies the intricacy of operations in a dynamic, consumer-facing retail environment.

Theoretical Conclusions. Theoretically, the research contributes to the understanding that LPO should be viewed as the interacting capability system comprising of several dimensions instead of the linear sequence of planning. Execution-quality dimensions like handling integrity, order accuracy, digital visibility, structured complaint resolution, build on classical Perfect Order Fulfillment and Logistics Service Quality by empirically showing that service recovery and quality assurance are inseparable control systems rather than after-sale auxiliaries. The robust development of flexibility proves responsiveness as well as adaptive-capacity theories by demonstrating that adaptability is systematically entrenched in logistics systems by designing policies, configuring assets, and routines of communication.

The research also reconceptualizes resilience as an operational state continuity that is manifested in infrastructure readiness, fleet upkeep, and data visibility as opposed to an episodic reaction that occurs once the disruption has taken place. The close overlap between monitoring and communication and recovery promotes the customer-focused theory of logistics, noting that information timeliness and responsiveness are the pillars of performance practice. Notably, the empirical data make the influence of digitalization more clear: technology magnifies and combines the already existing capabilities rather than causing performance by itself, which conforms to resource-based and complementarity views. In addition, sales-logistics integration is justified as information architecture on which omnichannel synchronization and recovery are supported and not only the coordination tool. The validated structure in combination demonstrates that logistics excellence is created through coherence of capabilities- quality assurance, flexibility, coordination, planning reliability, and recovery where planning offers direction but perpetual excellence is accomplished through disciplined execution and responsive flexibility.

Conclusions of Measurement Model. According to the scale-development view, the research findings demonstrate that the LPO measurement scheme has a sound conceptual underpinning but is still differentiated empirically, which necessitates a selective refinement instead of a complete redesign. The EFA phase fixed a consistent multi-dimensional structure and, with systematic purification, condensed indicators into coherent first-order constructs of Product Quality Assurance and Service Recovery (PQASR), Delivery Flexibility, Communication and Customer Coordination (DFCCC), Customer Relationship/Handling Controls (CRMPH), and Route Planning, Forecasting and Operational Reliability (RPFOR), and outcome-based LPO metrics of accuracy, condition and timeliness. The cumulative variance described is higher than traditional criteria of adequacy and it shows that the structural coverage of the domain of logistics performance is high.

The model has an overall measurement adequacy with varying strengths of constructs at the CFA stage. Areas of quality assurance, flexibility/communication, and customer-facing controls have high internal consistency, composite reliability, and adequate convergent validity, which indicate empirical strength. Conversely, planning and forecasting reliability domain has a relatively low reliability and AVE, which can be interpreted as the necessity of applying specific carefully selected and tailored wording and re-wording, or even individual item deletion, instead of construct deletion. The discriminant face of validity is fairly satisfactory, with the majority of the heterotrait-monotrait ratios falling within the recommended range, but the conceptual proximity of communication, infrastructure, and integration indicators is moderate, which does not indicate redundancy of measurement.

Distributional diagnostic tests and residual tests are within reasonable limits, and this indicates approximately normal statistics and the appropriateness of maximum likelihood estimation. The data quality and size suffice to perform advanced modeling and lack of deviations to ideal global fit can be explained by measurement specification and overlap of constructs rather than by a lack of data. Overall, the multidimensional structure of LPO is justifiable and justified by empirical evidence, having a number of highly tested constructs and others that have an opportunity of improvement through the repeated optimization. The model is thus prepared to be improved on a continuous basis instead of being discarded with the suggested recommendations based on the selective-deletion of items, rephrasing, and careful consolidation within overlapping areas. These specific improvements will enable the LPO measurement model to become more statistically robust with its theoretical depth and practical utility to the studies of retail and last-mile logistics intact.

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